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
- Part C - Waterflow Pipe

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)
```

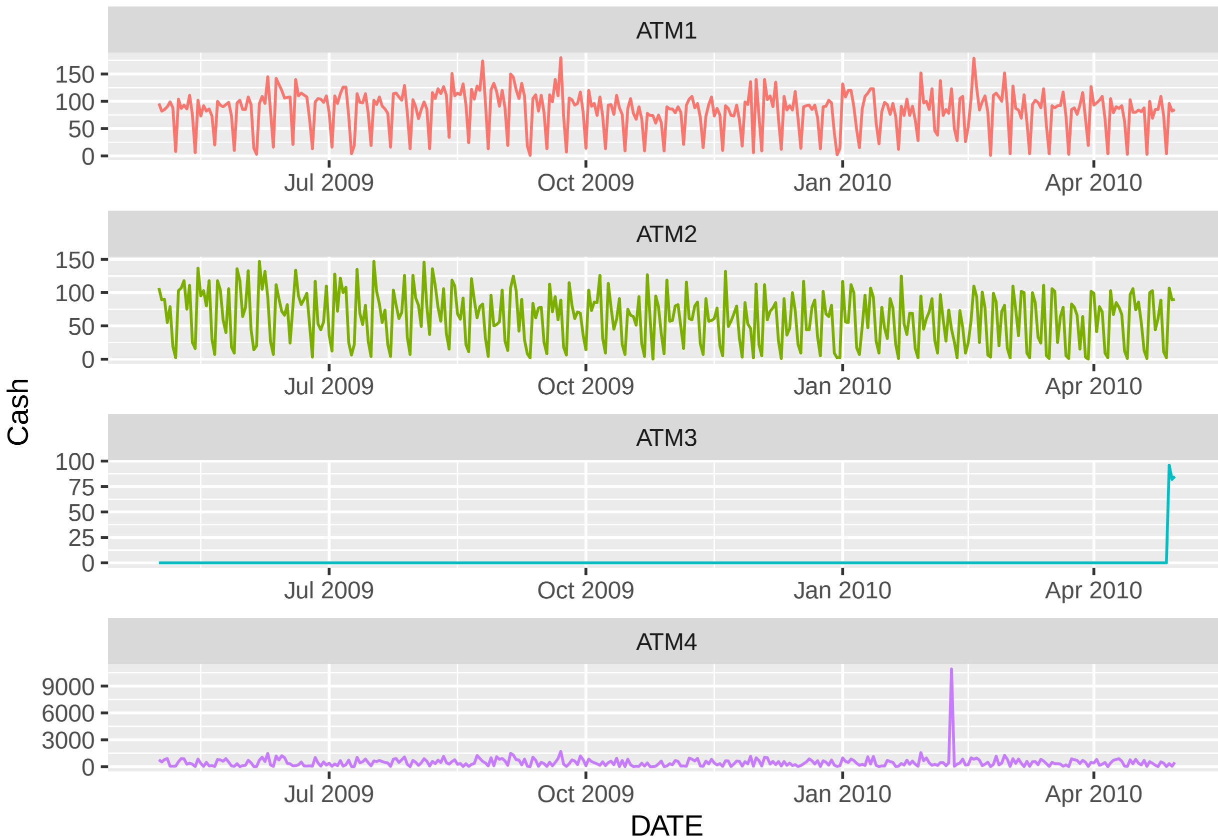
```
## Rows: 1,474
## Columns: 3
## $ DATE <dttm> 2009-05-01, 2009-05-01, 2009-05-02, 2009-05-02, 2009-05-03, 2009~
## $ ATM  <chr> "ATM1", "ATM2", "ATM1", "ATM2", "ATM1", "ATM2", "ATM1", "ATM2", "~
```

```
## $ Cash <dbl> 96, 107, 82, 89, 85, 90, 90, 55, 99, 79, 88, 19, 8, 2, 104, 103, ~
```

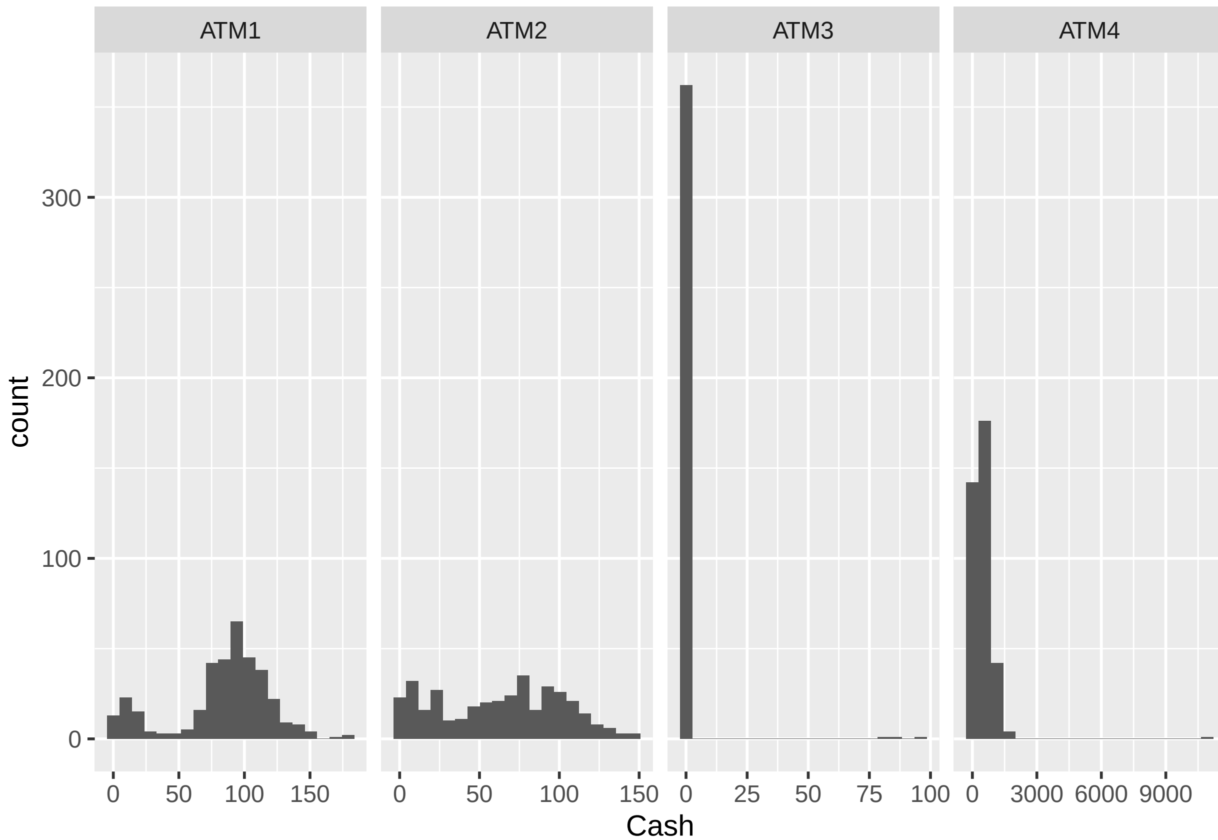
```r
# rows missing values
atm.data[!complete.cases(atm.data),]
```

```
## # 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
```

```r
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")
```




```r
# 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
```

```r
# 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.

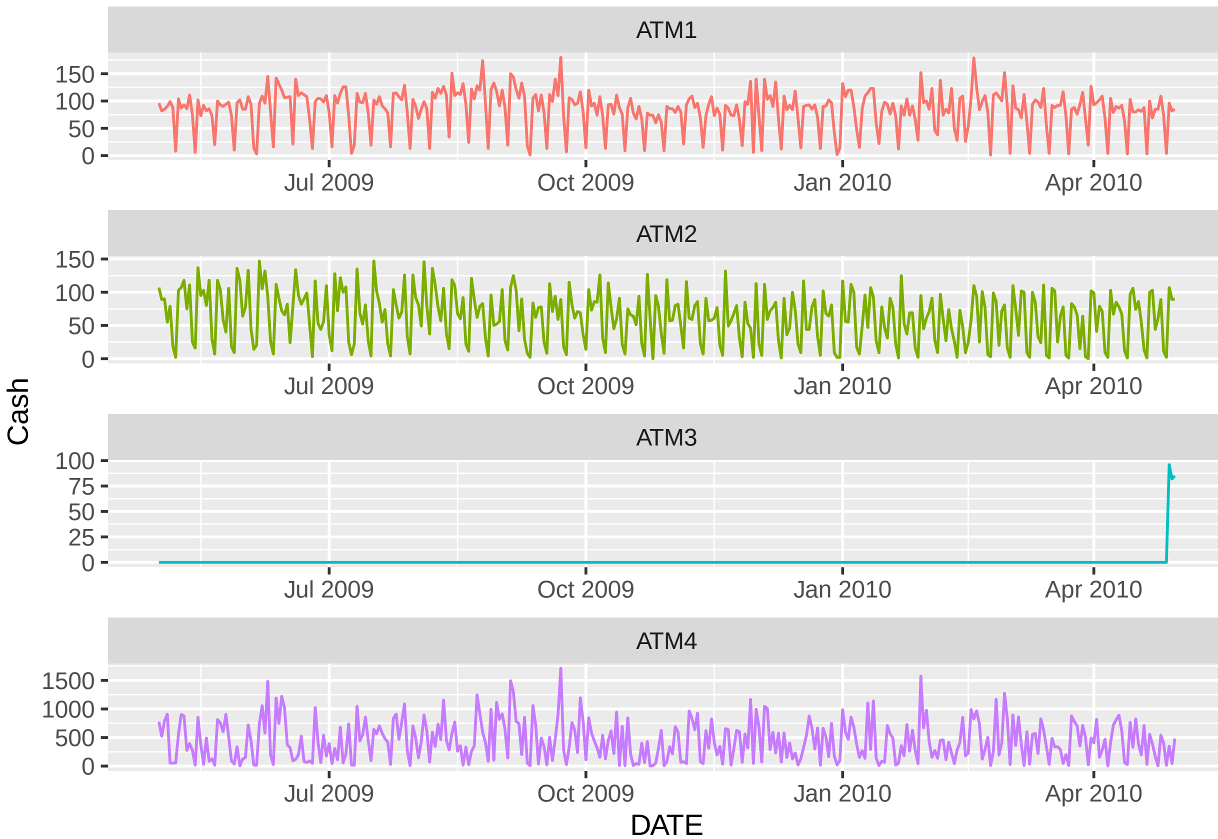
```
# convert into data frame, pivot longer , arrange by ATM and bind with dates
atm.new <- as.data.frame(atm.ts.cln) %>%
  pivot_longer(everything(), names_to = "ATM", values_to = "Cash") %>%
  arrange(ATM)

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
```

```
#library(xlsx)
#write.xlsx(atm.new, 'atmnew.xlsx', sheetName = "Sheet1", col.names = TRUE, row.names = TRUE, append = 
```

```
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

Function to plot forecast for various 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)

}
```

Function to calculate RMSEs for various models.

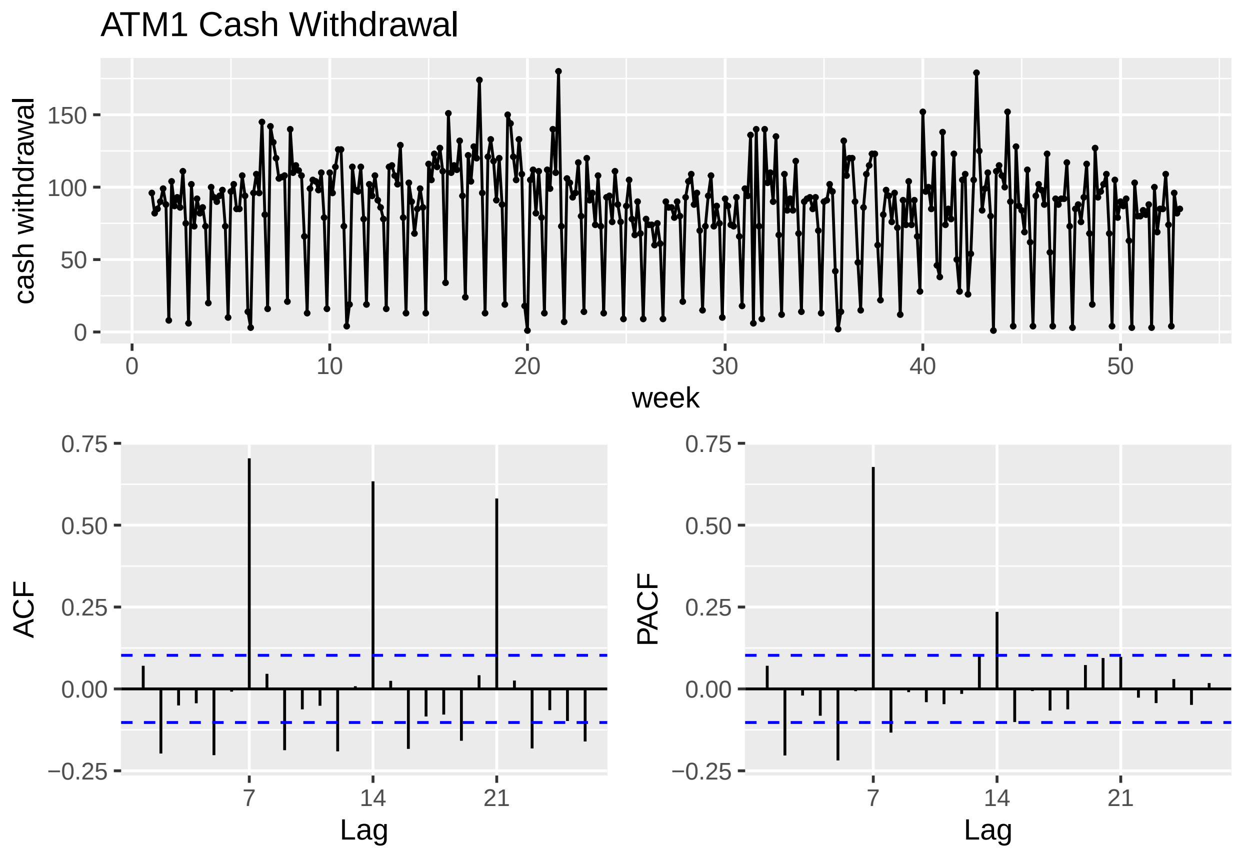
```
model_accuracy <- function(timeseries, atm_num) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)

  # models for forecast
  hw.model <- timeseries %>% hw(h=31, seasonal = "additive", lambda = lambda, damped = TRUE)
  ets.model <- timeseries %>% ets(lambda = lambda)

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


  # dataframe having rmse
  rmse = data.frame(RMSE=cbind(accuracy(hw.model)[,2],
                                  accuracy(ets.model)[,2],
                                  accuracy(arima.model)[,2]))
```

```
  names(rmse) = c("Holt-Winters", "ETS", "ARIMA")
  # display rmse
  rmse
}
```

ATM1

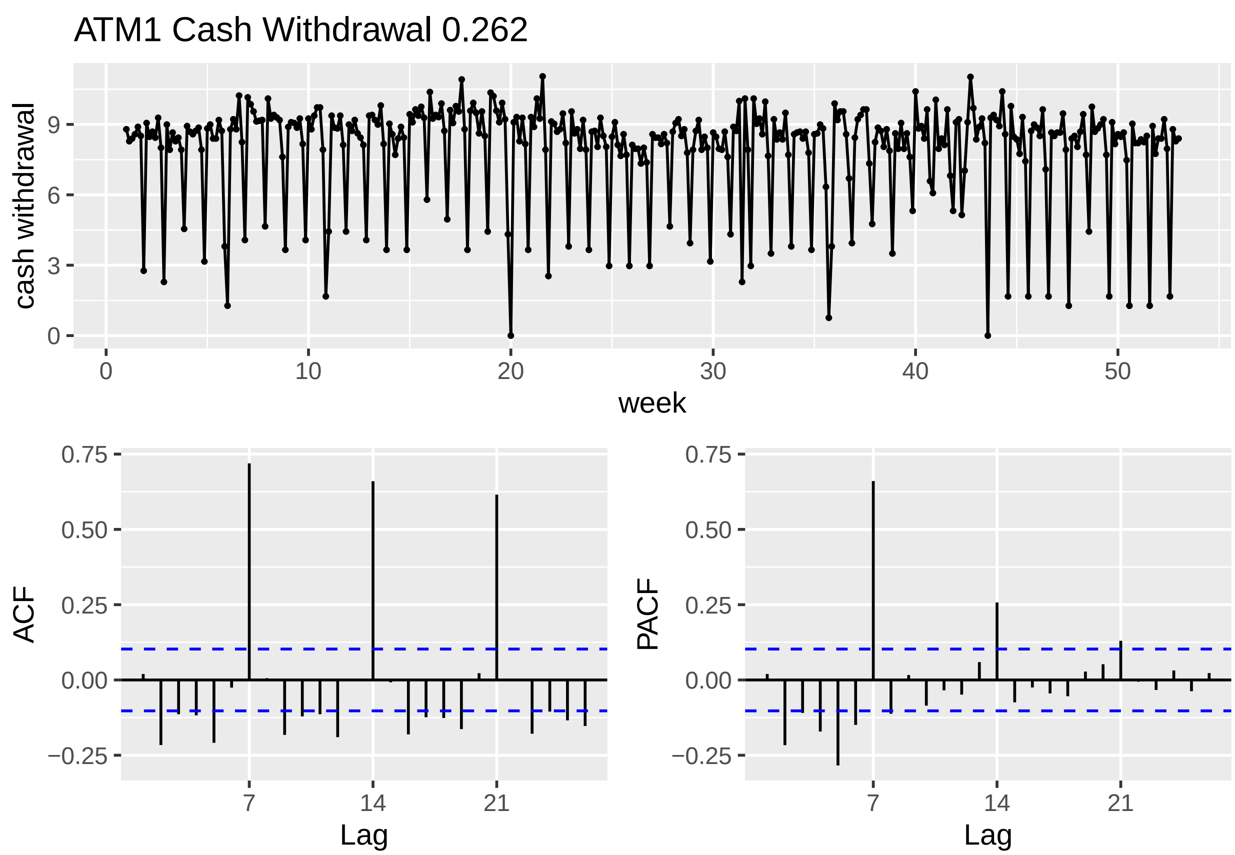
Seeing the time series plot, it is clear that there is a seasonality in the data. We can see increasing and decreasing activities over the weeks in below plot. From the ACF plot, we can see a slight decrease in every 7th lag due to trend. PACF plot shows some significant lags at the beginning.

```
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.

```
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
```




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

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

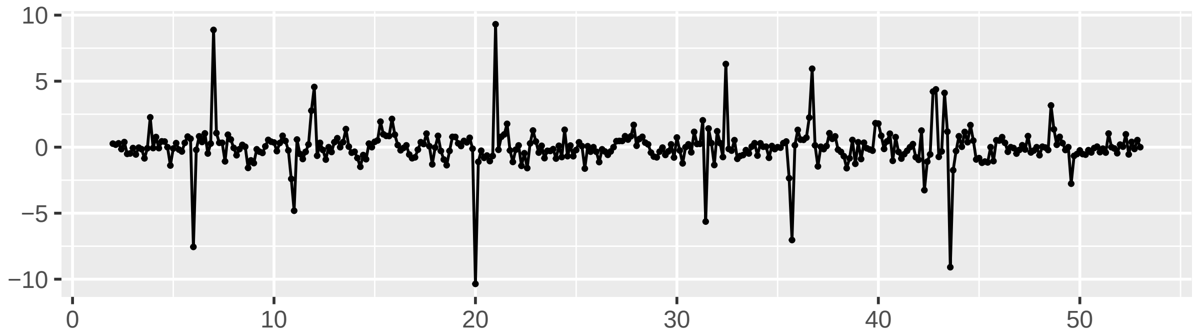
```r
# Number of differences required for a seasonally stationary series
nsdiffs(atm1.ts.bc)
```

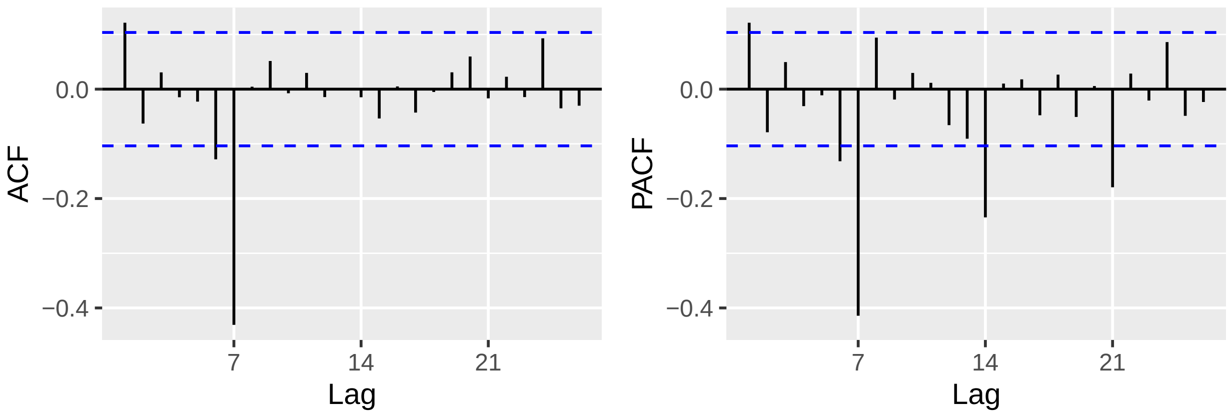
```
## [1] 1
```

```r
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
```

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






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

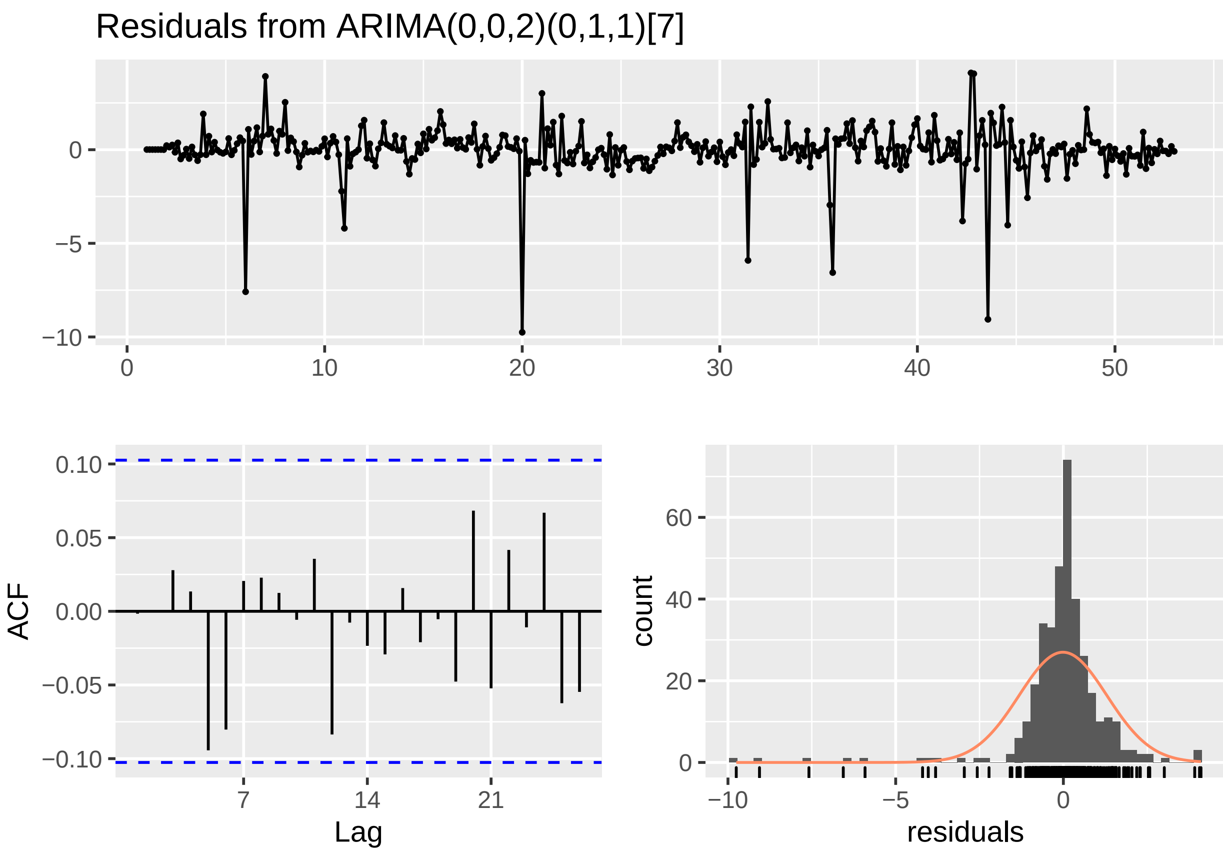
```
## ETS(A,N,A)
##
## Call:
##  ets(y = ., lambda = atm1.lambda)
##
##   Box-Cox transformation: lambda= 0.2616
##
##   Smoothing parameters:
##     alpha = 1e-04
##     gamma = 0.3513
##
##   Initial states:
##     l = 7.9717
##     s = -4.5094 0.5635 1.0854 0.5711 0.9551 0.5582
##            0.7761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

```
atm1.ts %>% auto.arima(lambda = atm1.lambda )
```

```
## 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
```

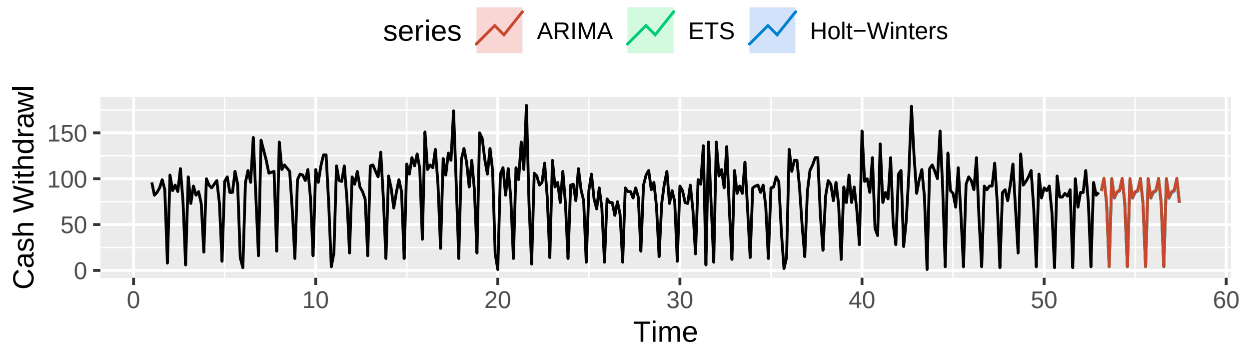
```
checkresiduals(atm1.ts %>% auto.arima(lambda = atm1.lambda ))
```

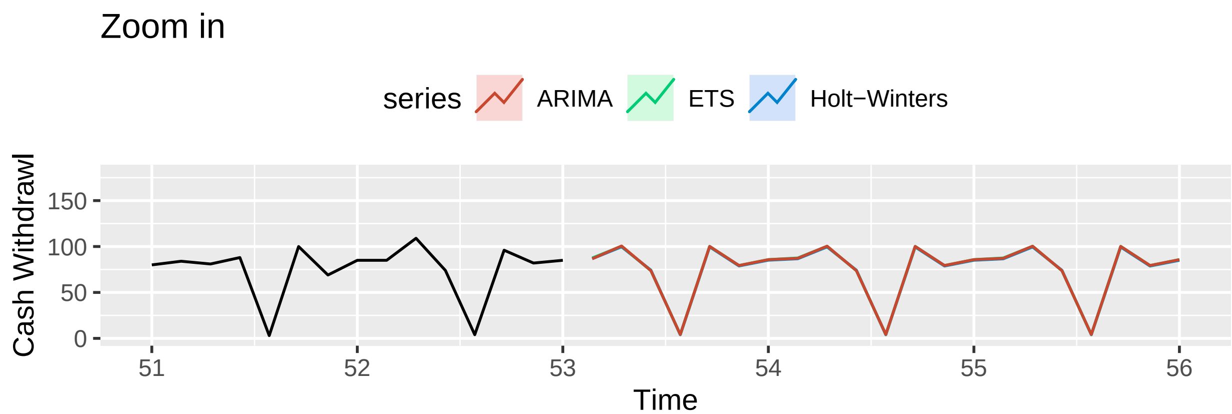



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,2)(0,1,1)[7]
## Q* = 9.8626, df = 11, p-value = 0.5428
##
## Model df: 3.   Total lags used: 14
```

```
atm.forecast(atm1.ts)
```

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



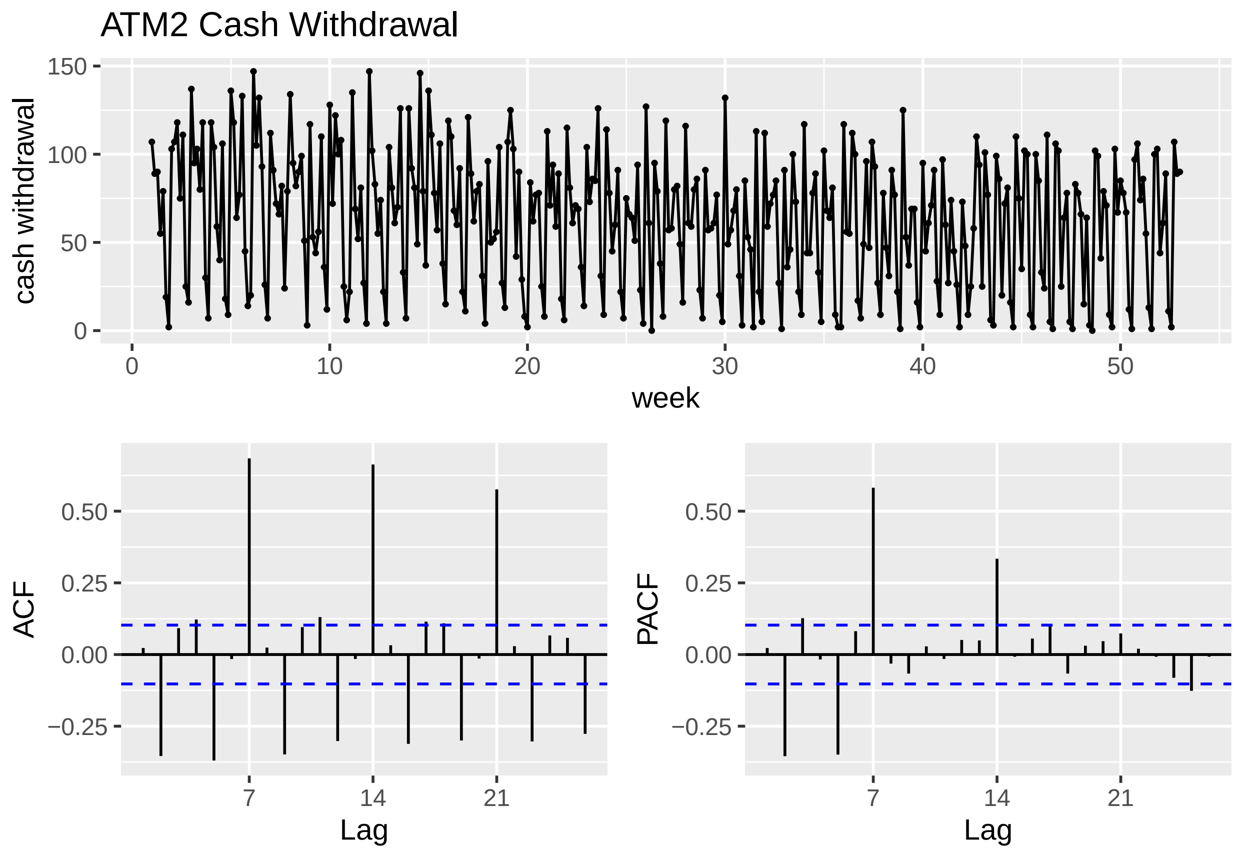



```
model_accuracy(atm1.ts,1)
```

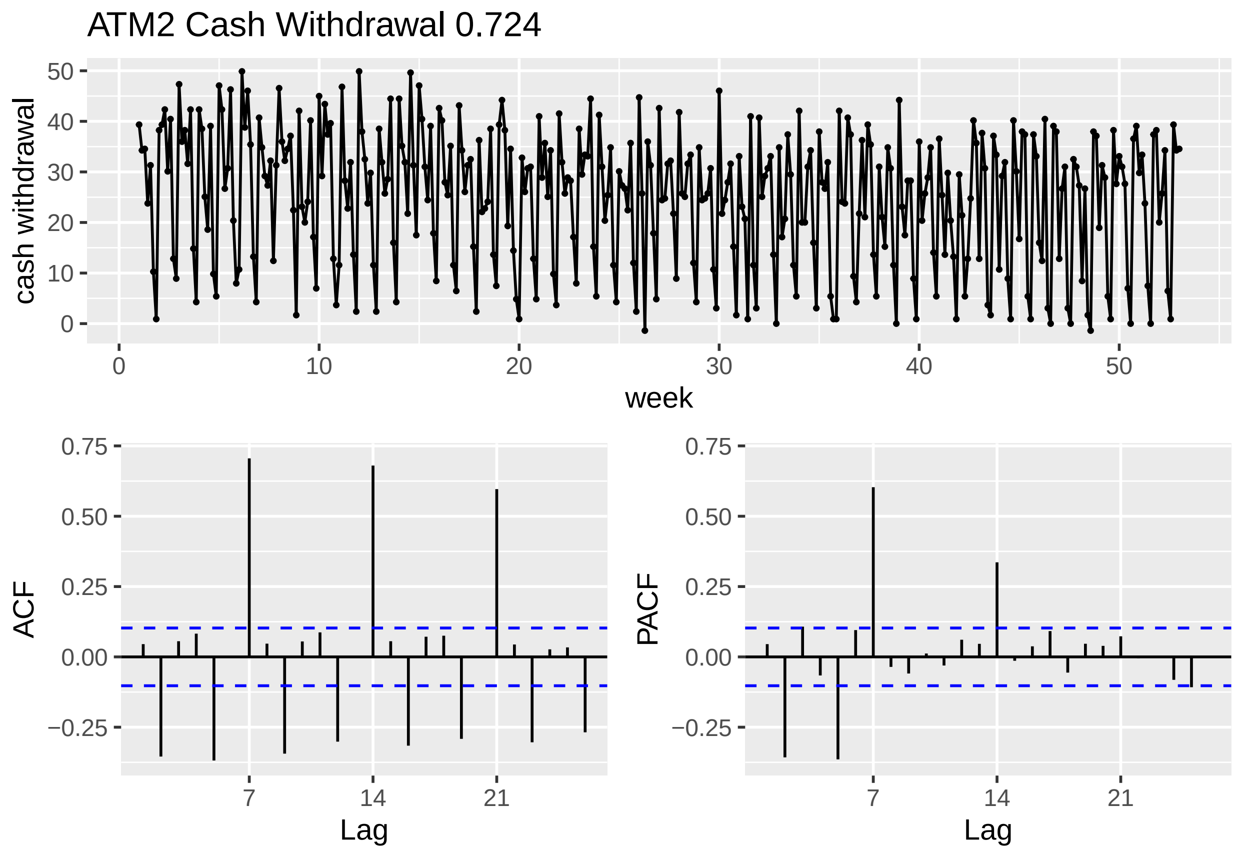
```
##   Holt-Winters      ETS    ARIMA
## 1     25.24631 24.92166 24.93069
```

ATM2

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




```
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
```

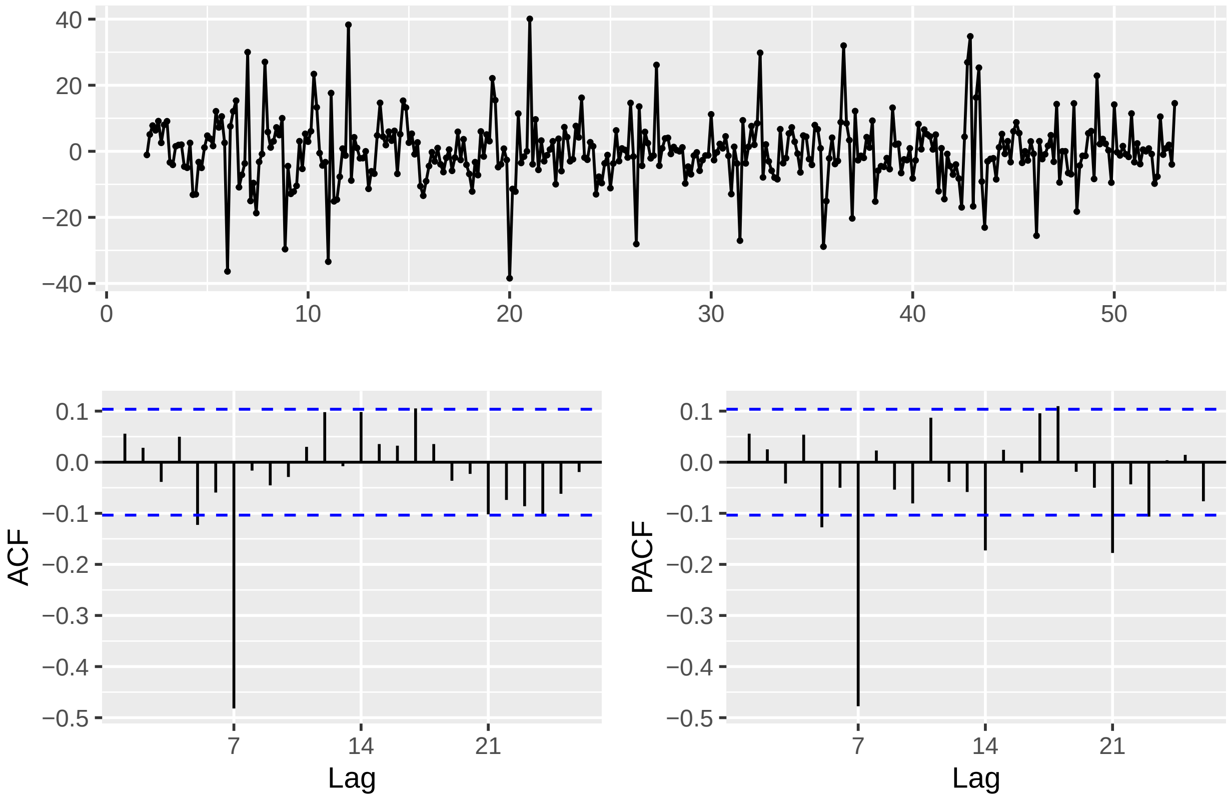
```r
# Number of differences required for a seasonally stationary series
nsdiffs(atm2.ts.bc)
```

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

```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
```

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

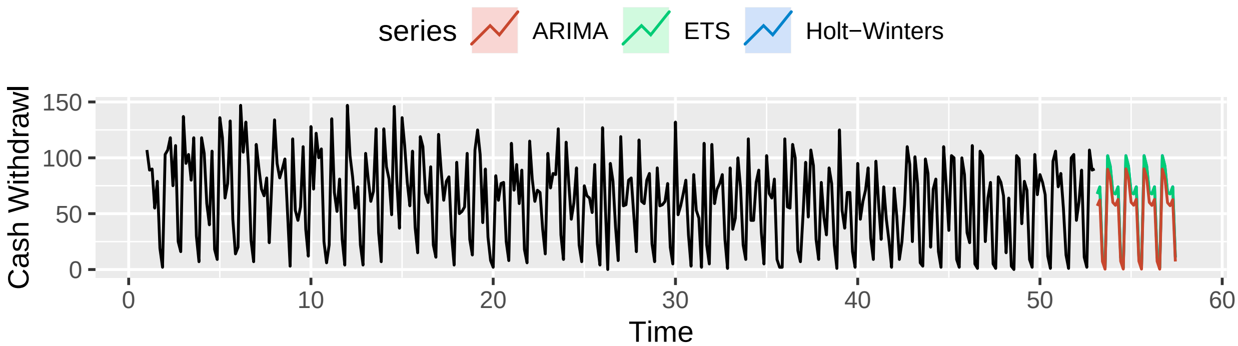


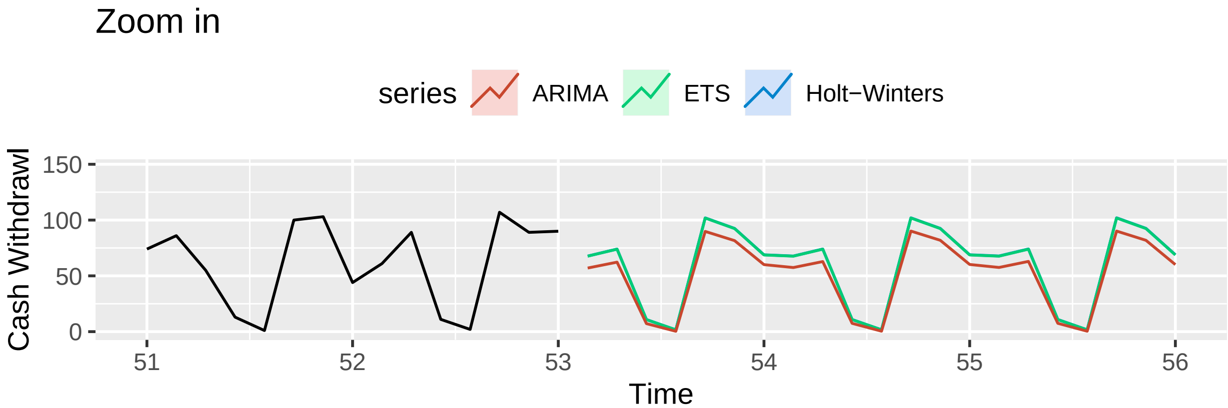

```r
atm2.ts %>% auto.arima(lambda = atm2.lambda )
```

```
## 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
```

```r
atm.forecast(atm2.ts)
```

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



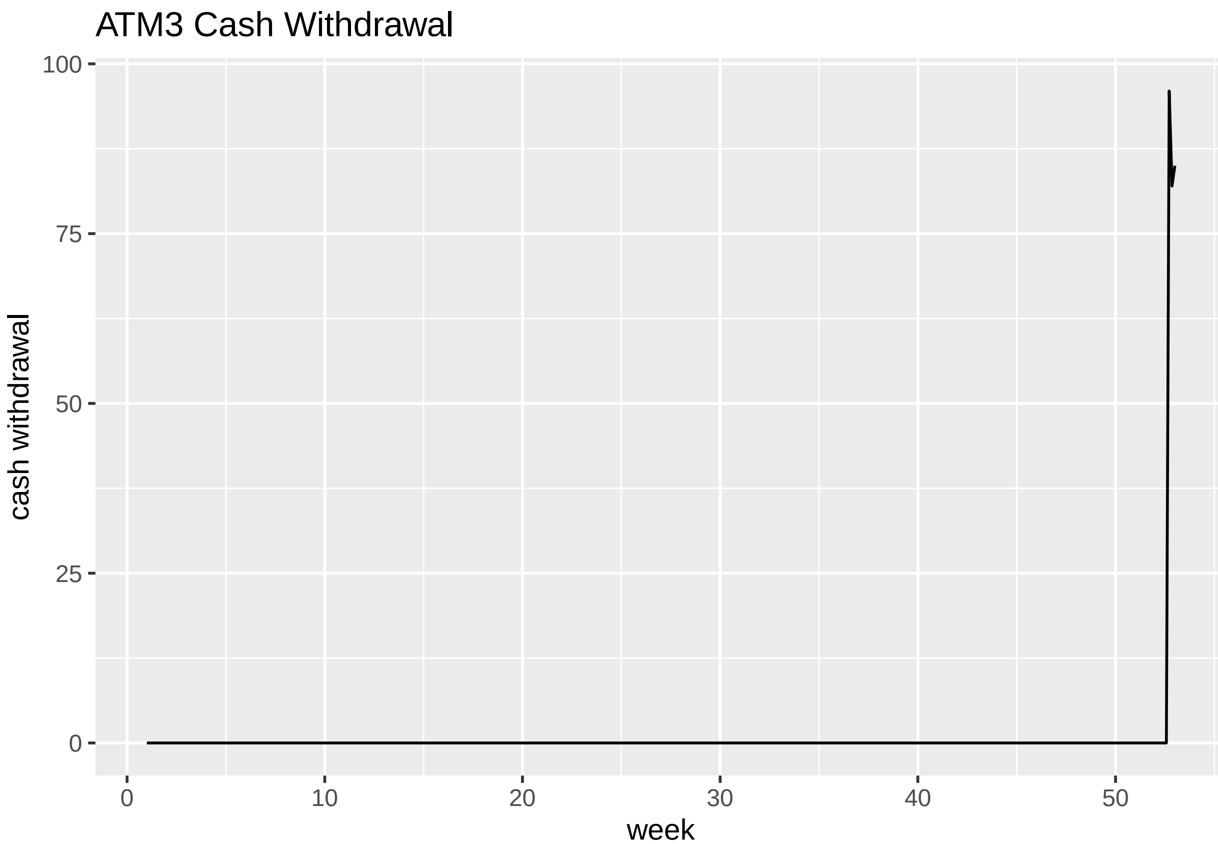



```
model_accuracy(atm2.ts,2)
```

```
##   Holt-Winters      ETS    ARIMA
## 1     25.44307 25.35721 24.27083
```

ATM3

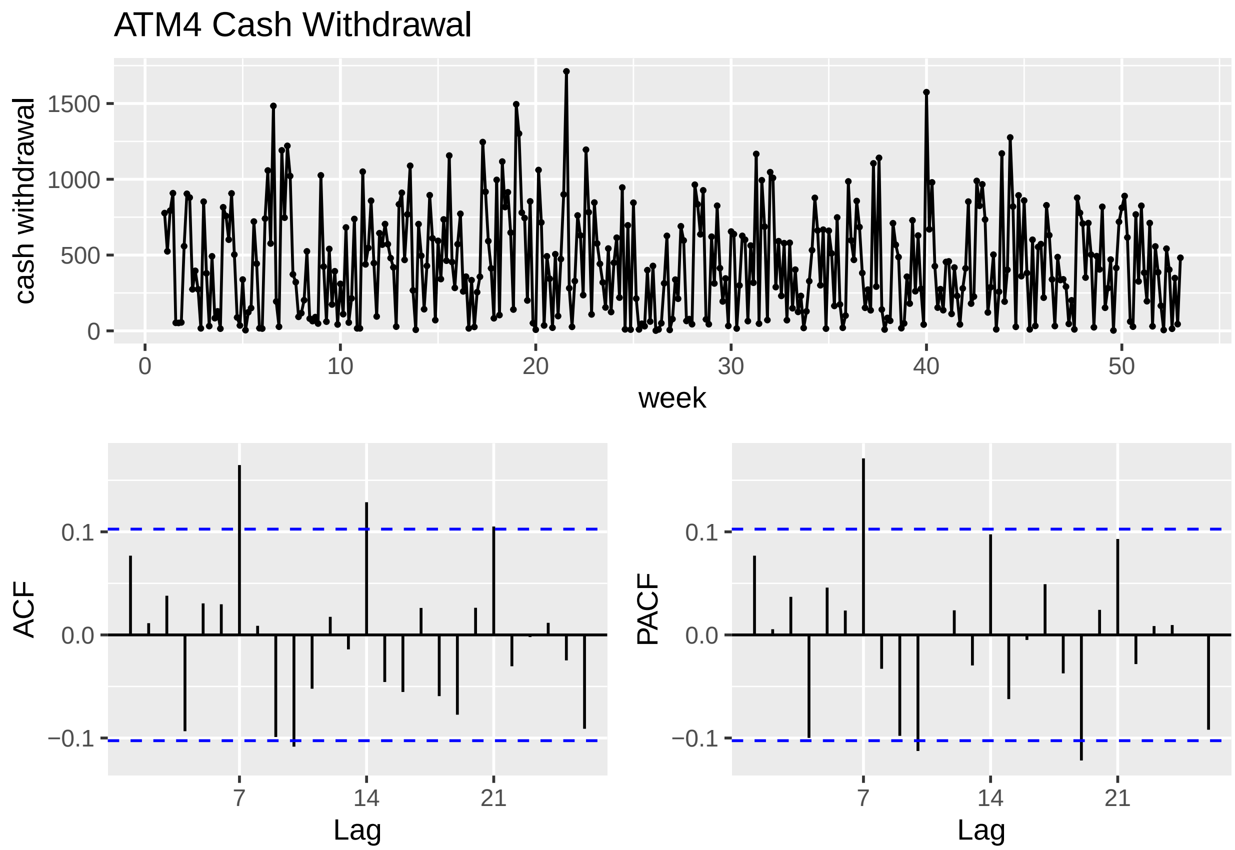
```
atm3.ts <- atm.new %>% filter(ATM=="ATM3") %>% select(Cash) %>% ts(frequency = 7)
autoplot(atm3.ts, main="ATM3 Cash Withdrawal", ylab="cash withdrawal", xlab="week")
```



ATM4

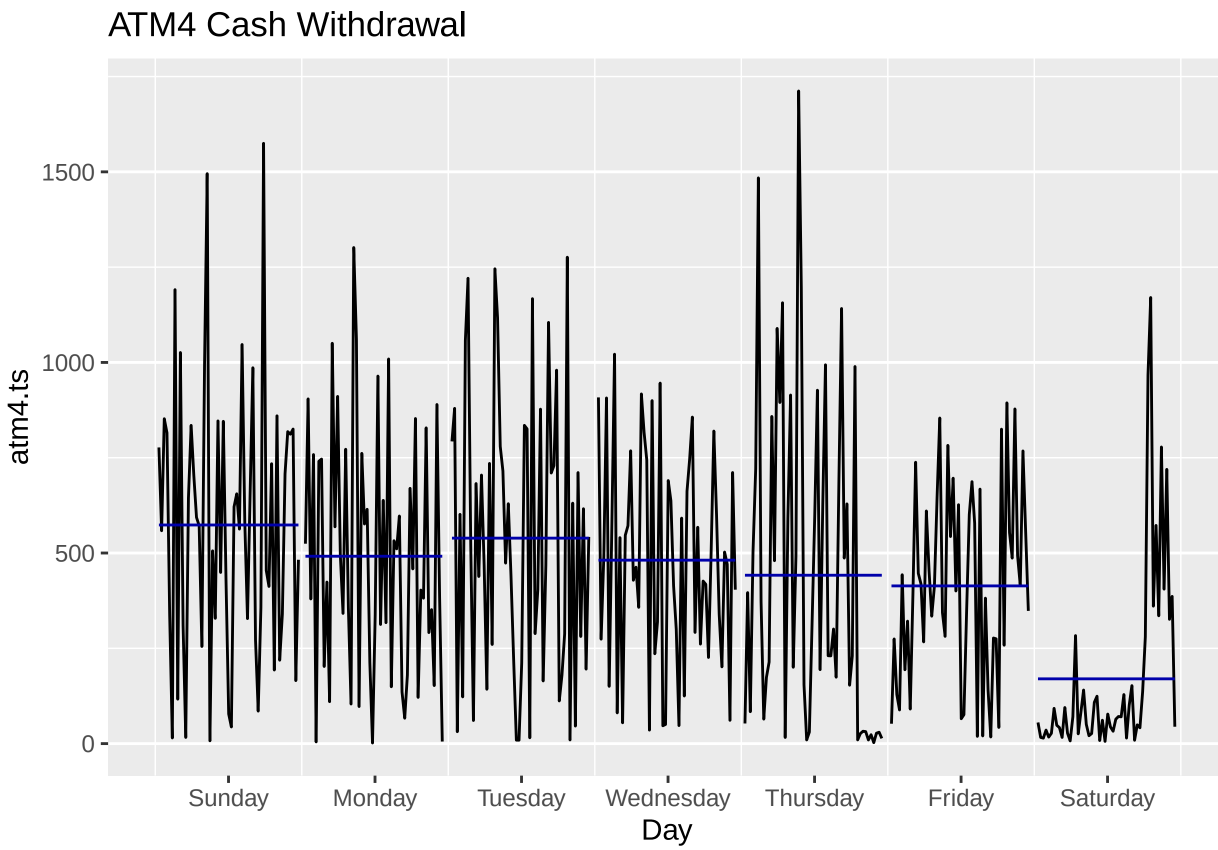
Seeing the time series plot, it is apparent that there is seasonality in this series. ACF shows a decrease in every 7th lag. From the PACF, there are few significant lags at the beginning but others within critical limit. Overall, it is non stationary, having seasonality and might require differencing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



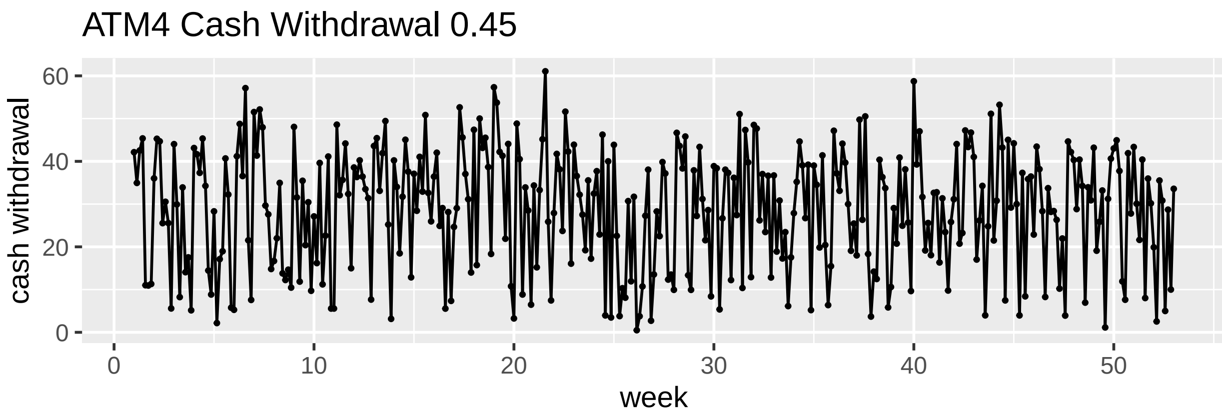
From the subseries plot, it is clear that Sunday is having highest mean for cash withdrawl while Saturday has the lowest.

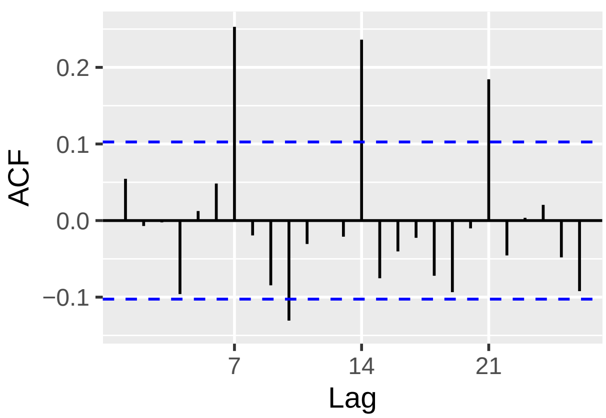
```
ggsubseriesplot(atm4.ts, main="ATM4 Cash Withdrawal")
```

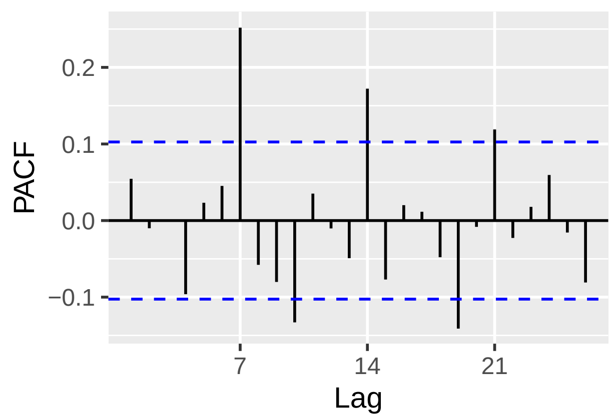


Next step is to apply BoxCox transformation. With λ being 0.45, the resulting transformation does handle the variablity in time series as shown in below transformed plot.

```
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
```

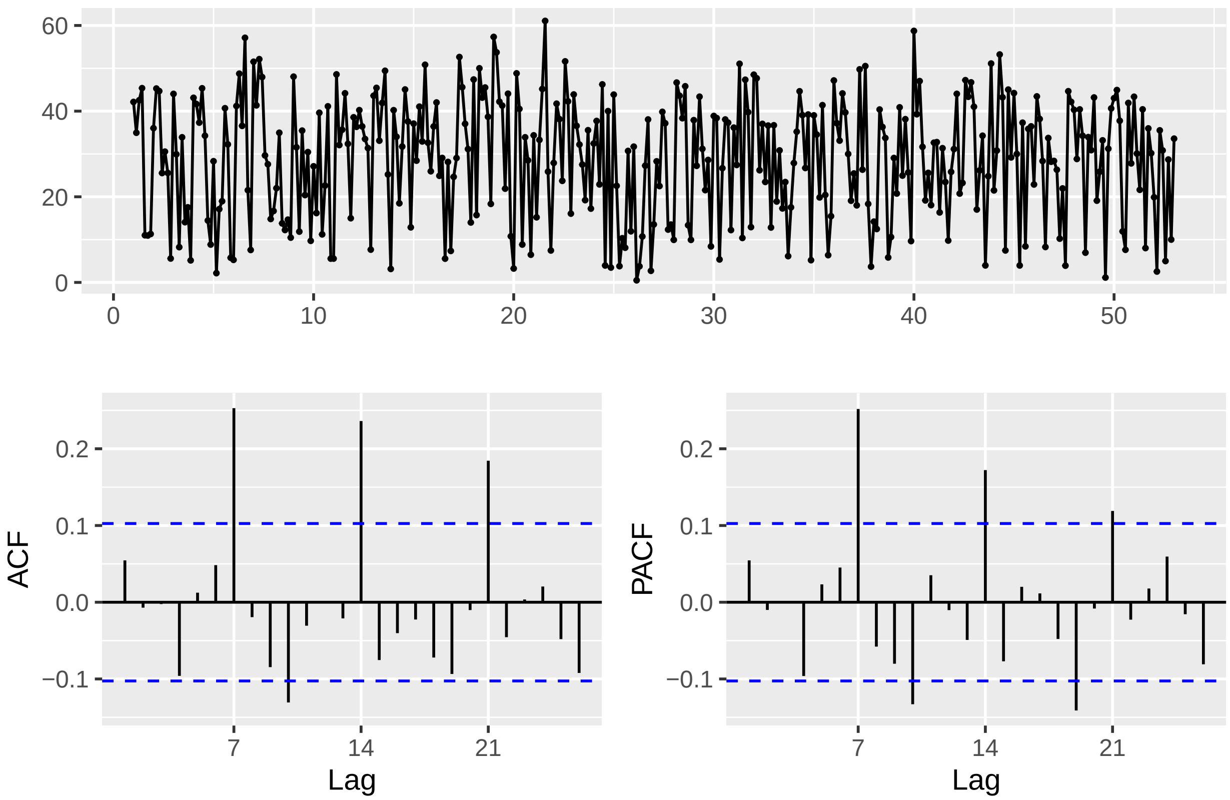
It shows number of differences required is 0 for boxcox transformed data.

```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.

```r
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.

```r
# 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.

```
# 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.

```
# Arima
atm4.ts %>% auto.arima(lambda = atm4.lambda)
```

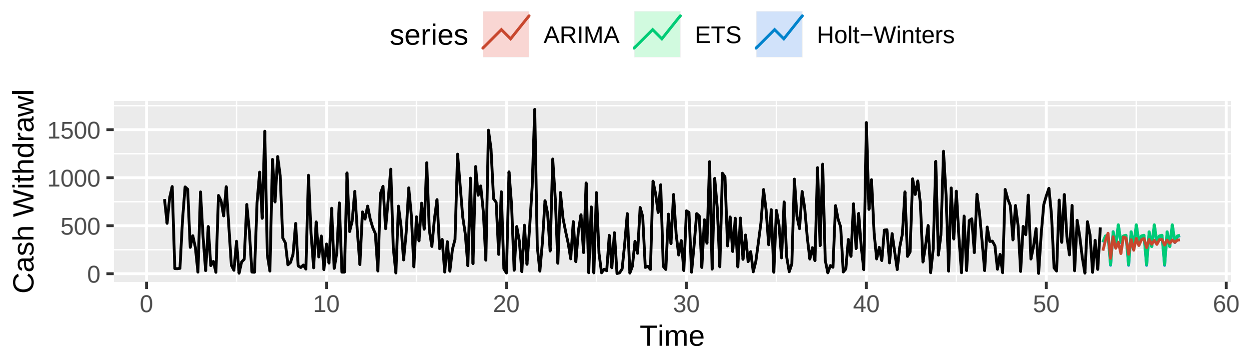
```
## Series: .
## ARIMA(0,0,1)(2,0,0)[7] with non-zero mean
## Box Cox transformation: lambda= 0.449771
##
## Coefficients:
##          ma1    sar1    sar2     mean
##       0.0790  0.2078  0.2023  28.6364
## s.e.  0.0527  0.0516  0.0525   1.2405
##
## sigma^2 estimated as 176.5:  log likelihood=-1460.57
```

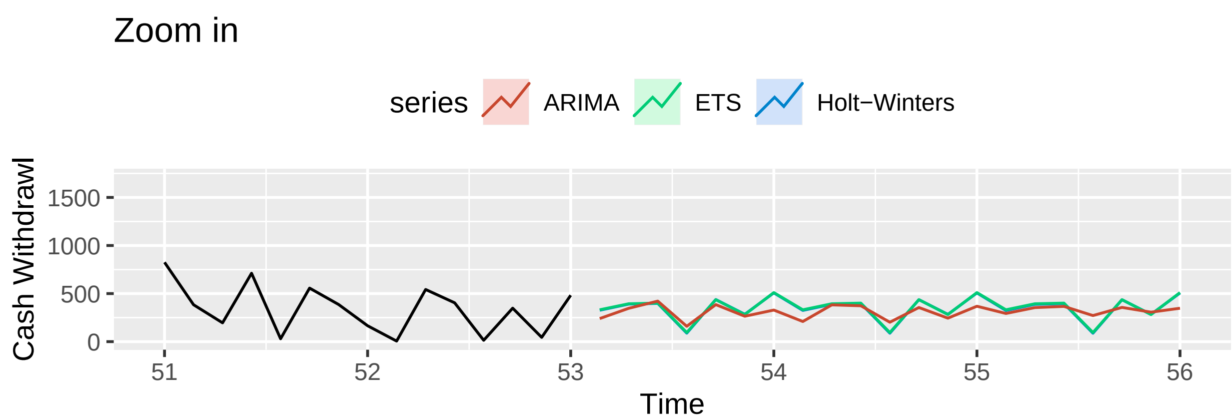
```
## AIC=2931.14   AICc=2931.3   BIC=2950.64
```

Next is to 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.

```
atm.forecast(atm4.ts)
```

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






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

```
##   Holt-Winters      ETS    ARIMA
## 1     340.8111 337.9663 351.9036
```

Part B - Forecasting Power

```
download.file(
  url="https://github.com/amit-kapoor/data624/blob/main/Project1/ResidentialCustomerForecastLoad-624.xl
  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
```

Part C - Waterflow Pipe

```
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"))
head(pipe1.data)
```

```
## # A tibble: 6 x 2
##   `Date Time`         WaterFlow
##   <dttm>                  <dbl>
## 1 2015-10-23 00:24:06     23.4
## 2 2015-10-23 00:40:02     28.0
## 3 2015-10-23 00:53:51     23.1
## 4 2015-10-23 00:55:40     30.0
## 5 2015-10-23 01:19:17      6.00
## 6 2015-10-23 01:23:58     15.9
```