Capestone Project

James Strayer

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Introduction

I was asked by a manager of Restaurant that does retail, to have a model to predict his sales for a given week, he gave me a file with the sales since end of March 2015. He started as the manager on 01-10-2018

Data import and cleaning

```
## Loading required package: tidyverse
```

```
## -- Attaching packages ---------------------------------------------------- tidyverse 1.2.1 --
```

```
## <U+2713> ggplot2 3.2.1     <U+2713> purrr   0.3.2
## <U+2713> tibble  2.1.3     <U+2713> dplyr   0.8.3
## <U+2713> tidyr   0.8.3     <U+2713> stringr 1.4.0
## <U+2713> readr   1.3.1     <U+2713> forcats 0.4.0
```

```
## -- Conflicts ------------------------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
## Parsed with column specification:
## cols(
##   Date = col_date(format = ""),
##   Weekday = col_character(),
##   Year = col_double(),
##   Month = col_character(),
##   Day = col_double(),
##   `annee fiscale` = col_character(),
##   Sales = col_number(),
##   Retail = col_number(),
##   TakeOutSales = col_number(),
##   Bar_Sales = col_number(),
##   Sales_Restaurant = col_number()
## )
```

```
## Observations: 1,715
## Variables: 11
## $ Date             <date> 2015-03-29, 2015-03-30, 2015-03-31, 2015-04-01, 201...
## $ Weekday          <chr> "SUNDAY", "MONDAY", "TUESDAY", "WEDNESDAY", "THURSDA...
## $ Year             <dbl> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015...
## $ Month            <chr> "March'15", "March'15", "March'15", "April'15", "Apr...
## $ Day              <dbl> 29, 30, 31, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1...
## $ `annee fiscale`  <chr> "2014-15", "2014-15", "2014-15", "2014-15", "2014-15...
## $ Sales            <dbl> 1792.00, NA, 1526.30, 2250.26, 2077.57, 2357.48, 150...
## $ Retail           <dbl> 373.00, NA, 380.95, 363.72, 268.80, 394.23, 476.17, ...
```

```
## $ TakeOutSales     <dbl> 0.00, 0.00, 99.25, 402.75, 0.00, 32.50, 93.73, 0.00,...
## $ Bar_Sales        <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 227....
## $ Sales_Restaurant <dbl> 1419.00, 0.00, 1046.10, 1483.79, 1808.77, 1930.75, 9...
```

The manager is using the data to have a day to day idea of the health of his buisness and therefore he added an accounting variable, annee fiscale (fiscal year) ,that we don't need and that we can remove.The Month variable is in a format not pratical for analysis (Month, YY) we want to have just the Full moth written without the year. So for simplicity and because we have the full date in the Date column, we are going to remove the month column as it is and create a new one based on the date column, we will do the same for the weekdays column. Furthermore we don't need the day number in our analysis so we will remove it too:

```
#Remove unncessary column for the analysis
DataForAnalysis<-DailySales%>%select(-Weekday,-Month,-Day,-`annee fiscale`)
#Add a column for weekday and month
DataForAnalysis<-DataForAnalysis%>%mutate(Weekday=weekdays(Date),Month=months(Date))
```

If we look again at the data we see that we have a Sales column, representing the Total Sales for the day and then each column after it, is the total sales for each day for each component of the restaurant possible sales revenu, so Retail, Take-out, Bar and Restaurant. We can see that there is NAs in all of those data

```
#looking for NAs in the sales data
sum(is.na(DataForAnalysis$Sales))
```

```
## [1] 175
```

```
sum(is.na(DataForAnalysis$Bar_Sales))
```

```
## [1] 208
```

```
sum(is.na(DataForAnalysis$Retail))
```

```
## [1] 188
```

```
sum(is.na(DataForAnalysis$TakeOutSales))
```

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

```
sum(is.na(DataForAnalysis$Sales_Restaurant))
```

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

we will change those NAs to 0, considering a $0 CAD sales for that day and variable

```
#Chaning NAs to 0 in the sales data
DataForAnalysis[is.na(DataForAnalysis$Sales),]$Sales<-0
DataForAnalysis[is.na(DataForAnalysis$Bar_Sales),]$Bar_Sales<-0
DataForAnalysis[is.na(DataForAnalysis$Retail),]$Retail<-0
DataForAnalysis[is.na(DataForAnalysis$TakeOutSales),]$TakeOutSales<-0
DataForAnalysis[is.na(DataForAnalysis$Sales_Restaurant),]$Sales_Restaurant<-0
```

Once we Cleaned the data. We are interested to add some classification for the days, specialy considering that holidays and special event should have an impact on the sales of a restaurant, to test this hypothesis we create a data frame event for all the bank holidays and events in the province of Quebec during the year:

here is an example of the data used to create that data frame: https://www.statutoryholidays.com/2017.php, all dates with observance National, QC and event such as Mother's day and Valentine's day. Once this vector is created we can create a new variable called EventDay which is true if the date equals one of the date in the vector

```
#Add a column for EventDay
DataForAnalysis<-DataForAnalysis%>%mutate(EventDay=ifelse(Date %in% Event,TRUE,FALSE))
```

Data exploration

```
#look at the structure of the data
glimpse(DataForAnalysis)
```

```
## Observations: 1,715
## Variables: 10
## $ Date             <date> 2015-03-29, 2015-03-30, 2015-03-31, 2015-04-01, 201...
## $ Year             <dbl> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015...
## $ Sales            <dbl> 1792.00, 0.00, 1526.30, 2250.26, 2077.57, 2357.48, 1...
## $ Retail           <dbl> 373.00, 0.00, 380.95, 363.72, 268.80, 394.23, 476.17...
## $ TakeOutSales     <dbl> 0.00, 0.00, 99.25, 402.75, 0.00, 32.50, 93.73, 0.00,...
## $ Bar_Sales        <dbl> 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00...
## $ Sales_Restaurant <dbl> 1419.00, 0.00, 1046.10, 1483.79, 1808.77, 1930.75, 9...
## $ Weekday          <chr> "Sunday", "Monday", "Tuesday", "Wednesday", "Thursda...
## $ Month            <chr> "March", "March", "March", "April", "April", "April"...
## $ EventDay         <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FAL...
```

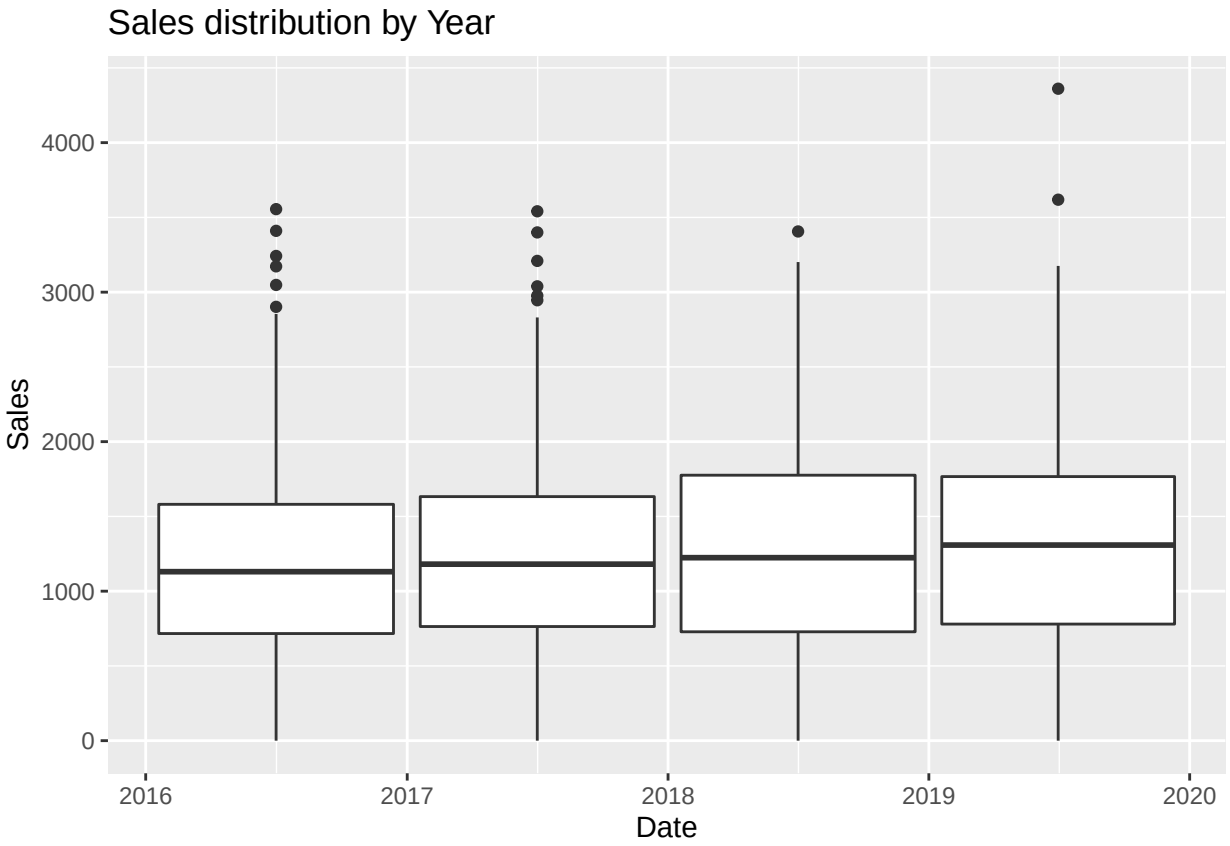
We want to have full years to have the same thing amount of days in the year to predict 2019 weeks. So we filter for 2016 and more

```
#Summary statistics for the variable
summary(DataForAnalysis)
```

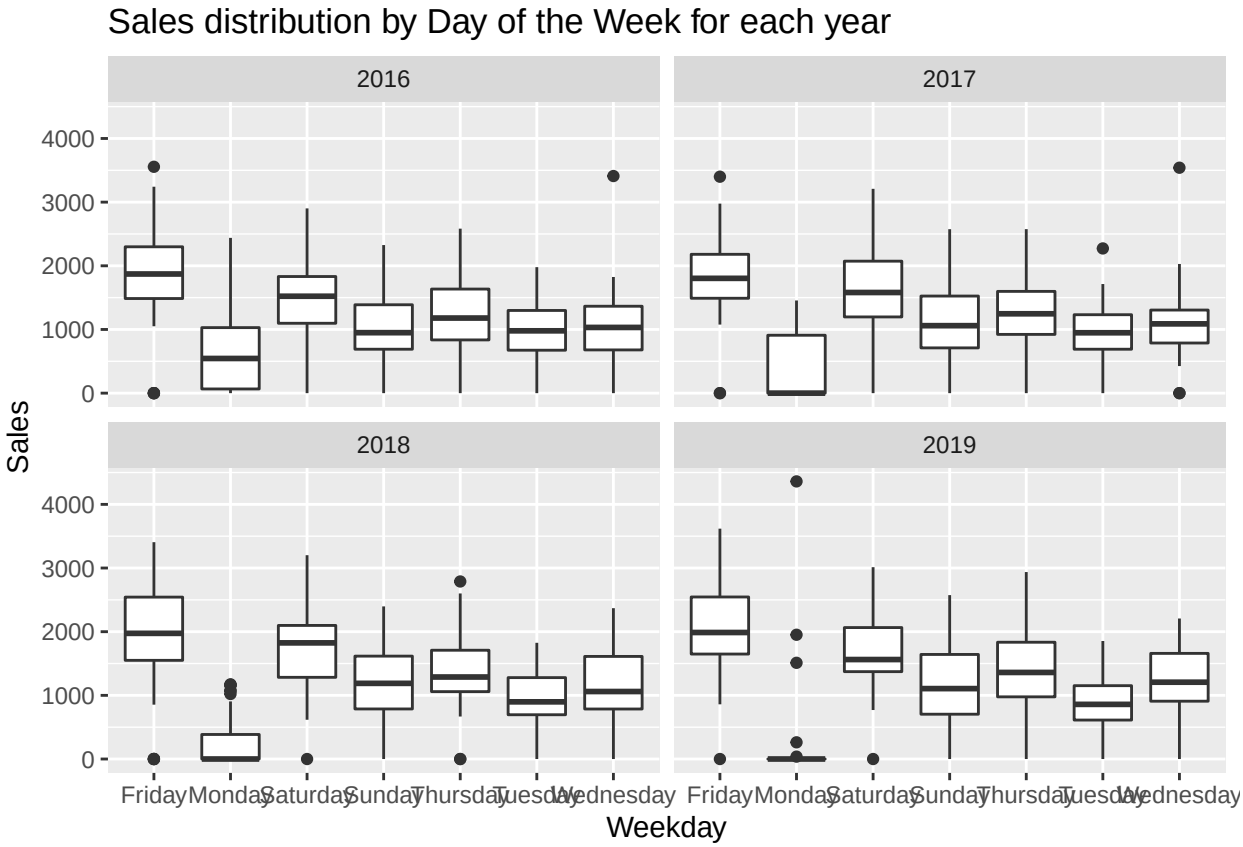
```
##       Date                 Year          Sales            Retail
##  Min.   :2016-01-01   Min.   :2016   Min.   :   0.0   Min.   :   0.0
##  1st Qu.:2016-12-25   1st Qu.:2016   1st Qu.: 756.8   1st Qu.: 160.2
##  Median :2017-12-19   Median :2017   Median :1212.2   Median : 257.7
##  Mean   :2017-12-19   Mean   :2017   Mean   :1229.4   Mean   : 266.5
##  3rd Qu.:2018-12-13   3rd Qu.:2018   3rd Qu.:1703.3   3rd Qu.: 367.9
##  Max.   :2019-12-29   Max.   :2019   Max.   :4360.8   Max.   :1436.9
##   TakeOutSales       Bar_Sales      Sales_Restaurant    Weekday
##  Min.   :   0.00   Min.   :   0.0   Min.   :-2299.8   Length:1437
##  1st Qu.:   0.00   1st Qu.:  70.0   1st Qu.:  358.0   Class :character
##  Median :  64.00   Median : 153.8   Median :  665.0   Mode  :character
##  Mean   :  83.85   Mean   : 177.0   Mean   :  702.0
##  3rd Qu.: 120.00   3rd Qu.: 257.5   3rd Qu.:  985.2
##  Max.   :2965.72   Max.   :1045.0   Max.   : 4284.2
##     Month            EventDay
##  Length:1437        Mode :logical
##  Class :character   FALSE:1437
##  Mode  :character
##
##
##
```

In our data set we have 10 variables for 1715 observations corresponding to the number of days the restaurant was open since the 29-03-2015.

Sales Variable



We see In the box plot above that 2019 was similar to 2018 in term of sales but with 2 outliers



In the box plot above we see that in 2019 they were very few Sales on Mondays and that the biggest are through the years were Thursday, Friday and Saturday. ##Preparing Data for Modeling I will be considering this data as a time series and such I will use a library made to handle them

```
## Loading required package: timetk
```

```
## Warning: package 'timetk' was built under R version 3.6.2
```

```
## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo
```

```
## Loading required package: forecast
```

```
## Warning: package 'forecast' was built under R version 3.6.2
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
## Registered S3 methods overwritten by 'forecast':
##   method             from
##   fitted.fracdiff    fracdiff
##   residuals.fracdiff fracdiff
```

```
## Loading required package: sweep
```

```
## Warning: package 'sweep' was built under R version 3.6.2
```

We then transform the data to train and test data and transform the train data into a time serie

```
## Loading required package: zoo
```

```
## Warning: package 'zoo' was built under R version 3.6.2
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
## Warning in set.seed(412, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

Modeling Data

ARIMA Model

We are going to test to 2 models to predict sales at a given week knowing the previous weeks. We will wan to try to predict the first week of 2019. We going to compare Linear Regression and ARIMA (Auto Regressive Integrated Moving Average) model (you can have a brief summary of ARIMA model here:https://machinelearningmastery.com/gentle-introduction-box-jenkins-method-time-series-forecasting/)

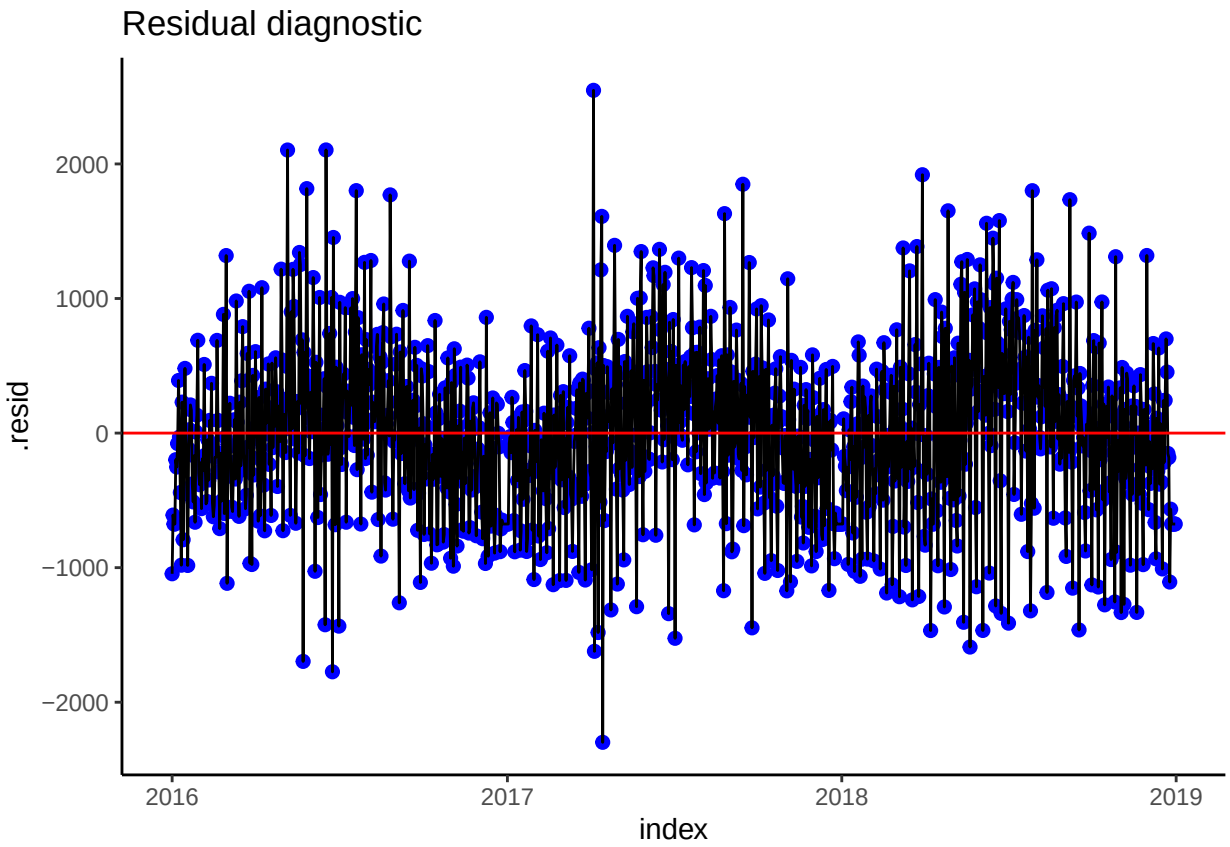
We use the forecast packages to use it:

```
## Warning in set.seed(412, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
## Series: ts_train
## ARIMA(2,0,0) with non-zero mean
##
## Coefficients:
##          ar1      ar2       mean
##       0.5438  -0.1033  1208.0598
## s.e.  0.0300   0.0301    34.3104
##
## sigma^2 estimated as 405360:  log likelihood=-8629.87
## AIC=17267.74   AICc=17267.78   BIC=17287.74
##
## Training set error measures:
##                      ME     RMSE      MAE  MPE MAPE      MASE         ACF1
## Training set 0.4771356 635.8073 494.3612 -Inf  Inf 0.8409041 -0.004392576
```

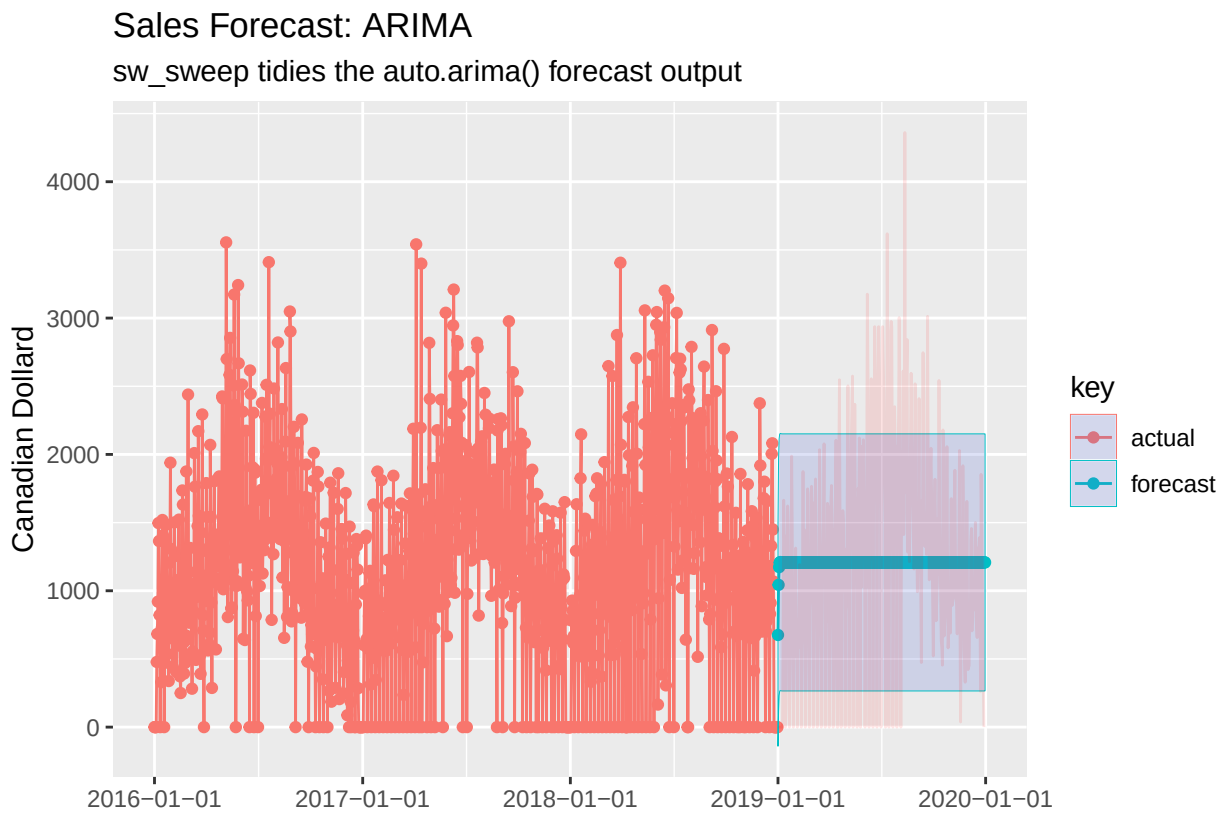
```
## # A tibble: 1,096 x 4
##    index      .actual .fitted  .resid
##    <date>       <dbl>   <dbl>   <dbl>
##  1 2016-01-01      0    1045. -1045.
##  2 2016-01-02      0     609.  -609.
##  3 2016-01-03      0     676.  -676.
##  4 2016-01-04      0     676.  -676.
##  5 2016-01-05    478.    676.  -198.
##  6 2016-01-06    683.    936.  -252.
##  7 2016-01-07    920.    998.   -78.0
##  8 2016-01-08   1496.   1106.   391.
##  9 2016-01-09   1365.   1395.   -29.9
## 10 2016-01-10    822.   1263.  -442.
## # ... with 1,086 more rows
```

We see that as we go forward in time the model tries to correct the residual but fails miserably get corrected by the mean of the previous days we can visualize the evolution of the residuals:



We then forecast for 2019

```
## # A tibble: 1,461 x 7
##    index      key    value lo.80 lo.95 hi.80 hi.95
##    <date>     <chr>  <dbl> <dbl> <dbl> <dbl> <dbl>
##  1 2016-01-01 actual    0     NA    NA    NA    NA
##  2 2016-01-02 actual    0     NA    NA    NA    NA
##  3 2016-01-03 actual    0     NA    NA    NA    NA
##  4 2016-01-04 actual    0     NA    NA    NA    NA
##  5 2016-01-05 actual  478.    NA    NA    NA    NA
##  6 2016-01-06 actual  683.    NA    NA    NA    NA
##  7 2016-01-07 actual  920.    NA    NA    NA    NA
##  8 2016-01-08 actual 1496.    NA    NA    NA    NA
##  9 2016-01-09 actual 1365.    NA    NA    NA    NA
## 10 2016-01-10 actual  822.    NA    NA    NA    NA
## # ... with 1,451 more rows
```




```
## # A tibble: 365 x 5
##    date       actual  pred  error error_pct
##    <date>      <dbl> <dbl>  <dbl>     <dbl>
##  1 2019-01-01      0   676.  -676.   -Inf
##  2 2019-01-02      0  1043. -1043.   -Inf
##  3 2019-01-03      0  1173. -1173.   -Inf
##  4 2019-01-04      0  1206. -1206.   -Inf
##  5 2019-01-05      0  1211. -1211.   -Inf
##  6 2019-01-06      0  1210. -1210.   -Inf
##  7 2019-01-07      0  1209. -1209.   -Inf
##  8 2019-01-08      0  1208. -1208.   -Inf
##  9 2019-01-09      0  1208. -1208.   -Inf
## 10 2019-01-10    786. 1208.  -422.    -0.536
## # ... with 355 more rows
```

Linear Regression

We take this time the all database and transform into a time serie before splitting into train and test set

```
## # A tibble: 1,437 x 38
##    Date        Year Sales Retail TakeOutSales Bar_Sales Sales_Restaurant Weekday
##    <date>     <dbl> <dbl>  <dbl>        <dbl>     <dbl>            <dbl> <chr>
##  1 2016-01-01  2016     0      0            0         0                0  Friday
##  2 2016-01-02  2016     0      0            0         0                0  Saturd...
##  3 2016-01-03  2016     0      0            0         0                0  Sunday
##  4 2016-01-04  2016     0      0            0         0                0  Monday
##  5 2016-01-05  2016   478.   261.          29.5      25.8             162. Tuesday
```

```
##  6 2016-01-06  2016  683.  189.          88       111               295. Wednes...
##  7 2016-01-07  2016  920.  102.          87.8     116               614. Thursd...
##  8 2016-01-08  2016 1496.  288.         102       262.              844. Friday
##  9 2016-01-09  2016 1365.  347.         114.      164               740. Saturd...
## 10 2016-01-10  2016  822.   96.6         26       121               578  Sunday
## # ... with 1,427 more rows, and 30 more variables: Month <chr>, EventDay <lgl>,
## #   index.num <int>, diff <int>, year <int>, year.iso <int>, half <int>,
## #   quarter <int>, month <int>, month.xts <int>, month.lbl <ord>, day <int>,
## #   hour <int>, minute <int>, second <int>, hour12 <int>, am.pm <int>,
## #   wday <int>, wday.xts <int>, wday.lbl <ord>, mday <int>, qday <int>,
## #   yday <int>, mweek <int>, week <int>, week.iso <int>, week2 <int>,
## #   week3 <int>, week4 <int>, mday7 <int>
```

We can know fit our training data

```
set.seed(42,sample.kind = "Rounding")
```

```
## Warning in set.seed(42, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
fit_Lr<-lm(Sales~.,data=select(trainLr_set,-Date))
summary(fit_Lr)
```

```
##
## Call:
## lm(formula = Sales ~ ., data = select(trainLr_set, -Date))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2364.85  -242.80     9.68   253.26  2497.16
##
## Coefficients: (31 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -2.233e+07  7.660e+07  -0.291 0.770728
## Year              4.853e+04  3.350e+04   1.448 0.147795
## WeekdayMonday    -1.036e+03  2.795e+02  -3.707 0.000221 ***
## WeekdaySaturday  -3.548e+02  8.537e+01  -4.156 3.50e-05 ***
## WeekdaySunday    -9.528e+02  1.464e+02  -6.510 1.15e-10 ***
## WeekdayThursday  -4.997e+02  8.718e+01  -5.731 1.30e-08 ***
## WeekdayTuesday   -6.070e+02  2.114e+02  -2.872 0.004161 **
## WeekdayWednesday -5.791e+02  1.464e+02  -3.954 8.18e-05 ***
## MonthAugust       1.459e+04  1.024e+04   1.424 0.154670
## MonthDecember     2.774e+04  2.046e+04   1.356 0.175544
## MonthFebruary    -7.126e+03  6.318e+03  -1.128 0.259620
## MonthJanuary     -1.084e+04  7.496e+03  -1.446 0.148475
## MonthJuly         1.104e+04  7.553e+03   1.461 0.144237
## MonthJune         7.605e+03  7.786e+03   0.977 0.328863
## MonthMarch       -3.668e+03  7.238e+03  -0.507 0.612461
## MonthMay          3.838e+03  3.829e+03   1.002 0.316472
## MonthNovember     2.448e+04  1.764e+04   1.388 0.165424
## MonthOctober      2.100e+04  1.519e+04   1.383 0.167083
## MonthSeptember    1.787e+04  1.357e+04   1.317 0.188141
## index.num        -3.550e-04  1.234e-03  -0.288 0.773618
## diff                     NA         NA      NA       NA
## year                     NA         NA      NA       NA
## year.iso         -3.719e+04  2.497e+04  -1.490 0.136643
```

```
## half                    NA         NA      NA       NA
## quarter                 NA         NA      NA       NA
## month                   NA         NA      NA       NA
## month.xts               NA         NA      NA       NA
## month.lbl.L             NA         NA      NA       NA
## month.lbl.Q             NA         NA      NA       NA
## month.lbl.C             NA         NA      NA       NA
## month.lbl^4             NA         NA      NA       NA
## month.lbl^5             NA         NA      NA       NA
## month.lbl^6             NA         NA      NA       NA
## month.lbl^7             NA         NA      NA       NA
## month.lbl^8             NA         NA      NA       NA
## month.lbl^9             NA         NA      NA       NA
## month.lbl^10            NA         NA      NA       NA
## month.lbl^11            NA         NA      NA       NA
## day               1.193e+02  1.279e+02   0.933 0.350980
## hour                    NA         NA      NA       NA
## minute                  NA         NA      NA       NA
## second                  NA         NA      NA       NA
## hour12                  NA         NA      NA       NA
## am.pm                   NA         NA      NA       NA
## wday                    NA         NA      NA       NA
## wday.xts                NA         NA      NA       NA
## wday.lbl.L              NA         NA      NA       NA
## wday.lbl.Q              NA         NA      NA       NA
## wday.lbl.C              NA         NA      NA       NA
## wday.lbl^4              NA         NA      NA       NA
## wday.lbl^5              NA         NA      NA       NA
## wday.lbl^6              NA         NA      NA       NA
## mday                    NA         NA      NA       NA
## qday            -9.500e-01  1.085e+02  -0.009 0.993013
## yday             3.196e+01  6.285e+01   0.508 0.611245
## mweek           -3.149e+00  1.895e+01  -0.166 0.868059
## week            -9.656e+01  5.611e+01  -1.721 0.085575 .
## week.iso        -7.223e+02  4.756e+02  -1.519 0.129119
## week2            1.089e+02  3.168e+01   3.437 0.000611 ***
## week3            1.990e+01  1.776e+01   1.121 0.262743
## week4           -3.182e+01  1.418e+01  -2.245 0.025004 *
## mday7           -1.338e+01  5.157e+01  -0.259 0.795304
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 467 on 1064 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.6066, Adjusted R-squared:  0.5955
## F-statistic: 54.68 on 30 and 1064 DF,  p-value: < 2.2e-16
```

Now we can predict

```
set.seed(42,sample.kind = "Rounding")
```

```
## Warning in set.seed(42, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
predict_lr<-predict(fit_Lr,newdata=select(testLr_set,-Date))
```

```
## Warning in predict.lm(fit_Lr, newdata = select(testLr_set, -Date)): prediction
## from a rank-deficient fit may be misleading
```

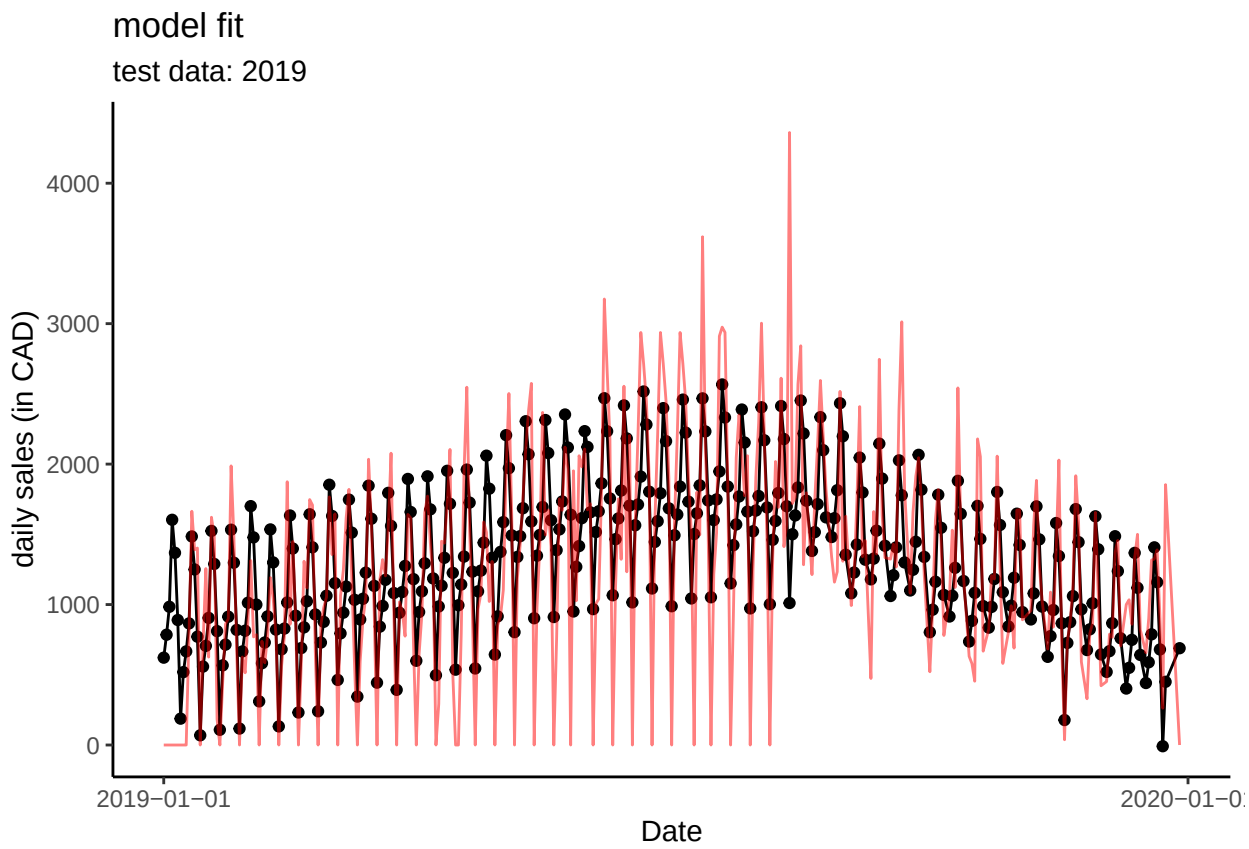
```
error_lr<-testLr_set%>%select(Date,actual=Sales)%>%
  mutate(pred=predict_lr,
         error=actual-predict_lr,
         error_pct=error/actual)
error_lr
```

```
## # A tibble: 341 x 5
##    Date       actual  pred   error error_pct
##    <date>      <dbl> <dbl>   <dbl>     <dbl>
##  1 2019-01-01      0   622.  -622.    -Inf
##  2 2019-01-02      0   785.  -785.    -Inf
##  3 2019-01-03      0   984.  -984.    -Inf
##  4 2019-01-04      0  1604. -1604.    -Inf
##  5 2019-01-05      0  1368. -1368.    -Inf
##  6 2019-01-06      0   890.  -890.    -Inf
##  7 2019-01-07      0   188.  -188.    -Inf
##  8 2019-01-08      0   519.  -519.    -Inf
##  9 2019-01-09      0   666.  -666.    -Inf
## 10 2019-01-10    786.  866.   -79.1    -0.101
## # ... with 331 more rows
```

```
dataToPlot<-testLr_set%>%add_column(pred=predict(fit_Lr,testLr_set)%>%tibble::enframe(name = NULL) %>% p
```

```
## Warning in predict.lm(fit_Lr, testLr_set): prediction from a rank-deficient fit
## may be misleading
```

```
dataToPlot %>%
 ggplot(aes(x = Date, y = pred)) +
 geom_line() +
geom_point()+
geom_line(data = testLr_set,aes(x=Date,y=Sales),color="red",alpha=0.5)+
 scale_x_date(date_breaks = "1 year", date_labels = "%F") +
 scale_color_manual(
  values = c(
   "weekly_sales" = "black",
   "lm_pred" = "#fdc7d7"
  )
 ) +
 theme_classic() +
 labs(title = "model fit",
  subtitle = "test data: 2019",
  x = "Date",
  y = "daily sales (in CAD)"
  )
```



On the plot abobe we see in red The actual value of sales and in black the prediction made by the linear regression model.

Discussion

In conclusion, we see that the linear regression has a better accuracy than the ARIMA model for predicting the sales for 2019. Both these models could be improved by splitting the data on weekdays and looking at the sales by weekday. We saw that the restaurant was not open on (made no sales) Monday for 2019. When comparing the sales by year we see that 2019 was similar in term of sales to the other year with only 341 days opened instead of 365 days. It might be interesting to predict the sales for 2019 considering the full 365 days.