Anomally Detection

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2022-06-10

Specific Objective

We have also been requested to check whether there are any anomalies in the given sales dataset. The objective of this task being fraud detection.

Loading Reuired Libraries

```
# loading libraries
library(data.table)
library(ggplot2)
library(tibble)
library(tibbletime)
```

```
##
## Attaching package: 'tibbletime'

## The following object is masked from 'package:stats':
##
##     filter
```

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v tidyr   1.2.0     v dplyr   1.0.9
## v readr   2.1.2     v stringr 1.4.0
## v purrr   0.3.4     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::between()   masks data.table::between()
## x dplyr::filter()    masks tibbletime::filter(), stats::filter()
## x dplyr::first()     masks data.table::first()
## x dplyr::lag()       masks stats::lag()
## x dplyr::last()      masks data.table::last()
## x purrr::transpose() masks data.table::transpose()
```

```
library(anomalize)
```

```
## == Use anomalize to improve your Forecasts by 50%! ==============================
## Business Science offers a 1-hour course - Lab #18: Time Series Anomaly Detection!
## </> Learn more at: https://university.business-science.io/p/learning-labs-pro </>
```

```
library(dbplyr)
```

```
##
## Attaching package: 'dbplyr'
```

```
## The following objects are masked from 'package:dplyr':
##
##     ident, sql
```

```
library(timetk)
```

```
##
## Attaching package: 'timetk'
```

```
## The following object is masked from 'package:data.table':
##
##     :=
```

```
library(tibble)
library(mvtnorm)
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(psych)
```

```
##
## Attaching package: 'psych'
```

```
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```
library(tibbletime)
library(data.table)
library(dplyr)
```

Reading our Dataset from the URL provided

```
df<- read.csv("http://bit.ly/CarreFourSalesDataset")
#Lets preview the head
head(df)
```

```
##        Date    Sales
## 1  1/5/2019 548.9715
## 2  3/8/2019  80.2200
## 3  3/3/2019 340.5255
## 4 1/27/2019 489.0480
## 5  2/8/2019 634.3785
## 6 3/25/2019 627.6165
```

```
tail(df)
```

```
##           Date     Sales
## 995  2/18/2019   63.9975
## 996  1/29/2019   42.3675
## 997   3/2/2019 1022.4900
## 998   2/9/2019   33.4320
## 999  2/22/2019   69.1110
## 1000 2/18/2019  649.2990
```

```
summary(df)
```

```
##      Date               Sales
##  Length:1000        Min.   :  10.68
##  Class :character   1st Qu.: 124.42
##  Mode  :character   Median : 253.85
##                     Mean   : 322.97
##                     3rd Qu.: 471.35
##                     Max.   :1042.65
```

```
dim(df)
```

```
## [1] 1000    2
```

###Checking for Nan Values

```
colSums(is.na(df))
```

```
##  Date Sales
##     0     0
```

```
#Displaying the Data structure
str(df)
```

```
## 'data.frame':    1000 obs. of  2 variables:
##  $ Date : chr  "1/5/2019" "3/8/2019" "3/3/2019" "1/27/2019" ...
##  $ Sales: num  549 80.2 340.5 489 634.4 ...
```

Converting the Date column into a Datime object type

```
df$Date <- as.Date(df$Date, format = "%m/%d/%Y")
df$Date <- sort(df$Date, decreasing = FALSE)
str(df)
```

```
## 'data.frame':    1000 obs. of  2 variables:
##  $ Date : Date, format: "2019-01-01" "2019-01-01" ...
##  $ Sales: num  549 80.2 340.5 489 634.4 ...
```

```
df$Date <- as.POSIXct(df$Date)
```

```
df <- as_tibble(df)
```

Time Series Decomposition

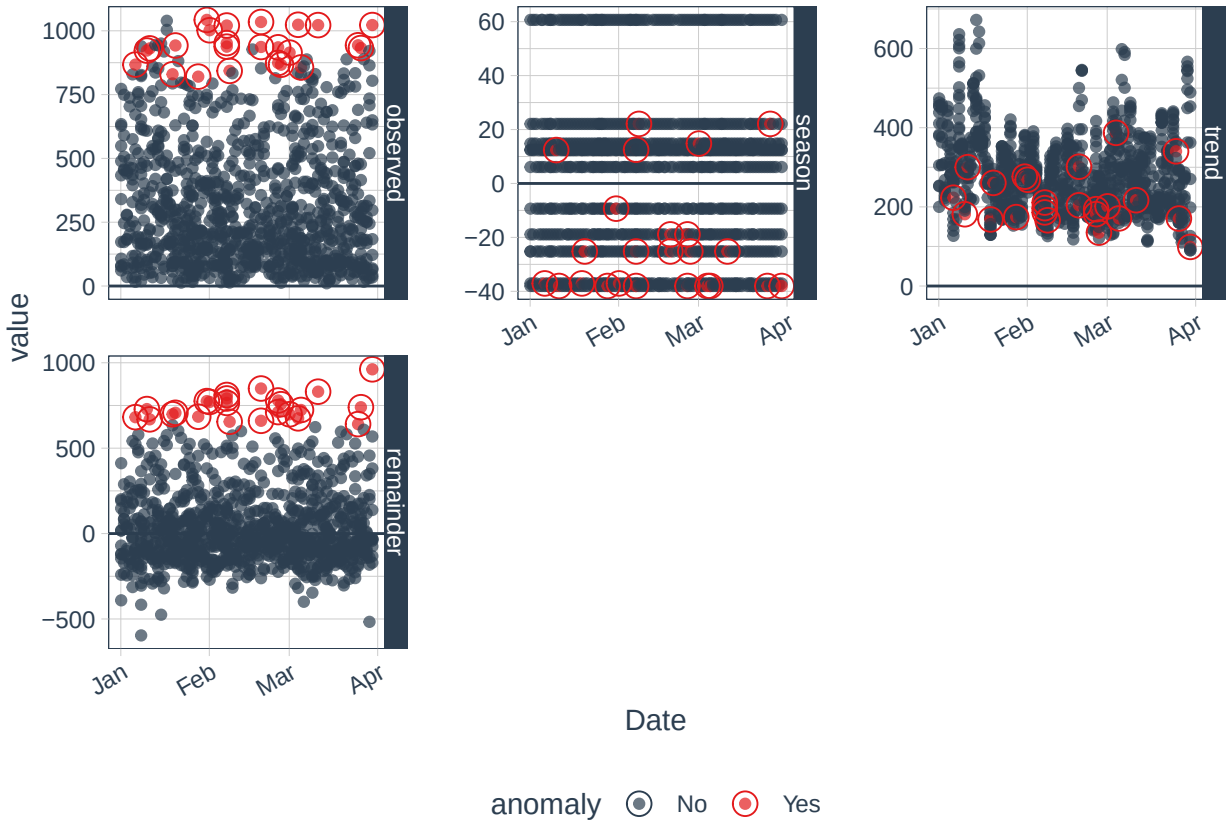
```
df %>%
time_decompose(Sales, method = 'stl', frequency = 'auto', trend = 'auto') %>%
anomalize(remainder, method = 'gesd', alpha = 0.1, max_anoms = 0.5) %>%
plot_anomaly_decomposition(ncol = 3, alpha_dots = 0.7)
```

```
## Converting from tbl_df to tbl_time.
## Auto-index message: index = Date
```

```
## frequency = 11 seconds
```

```
## trend = 11 seconds
```

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



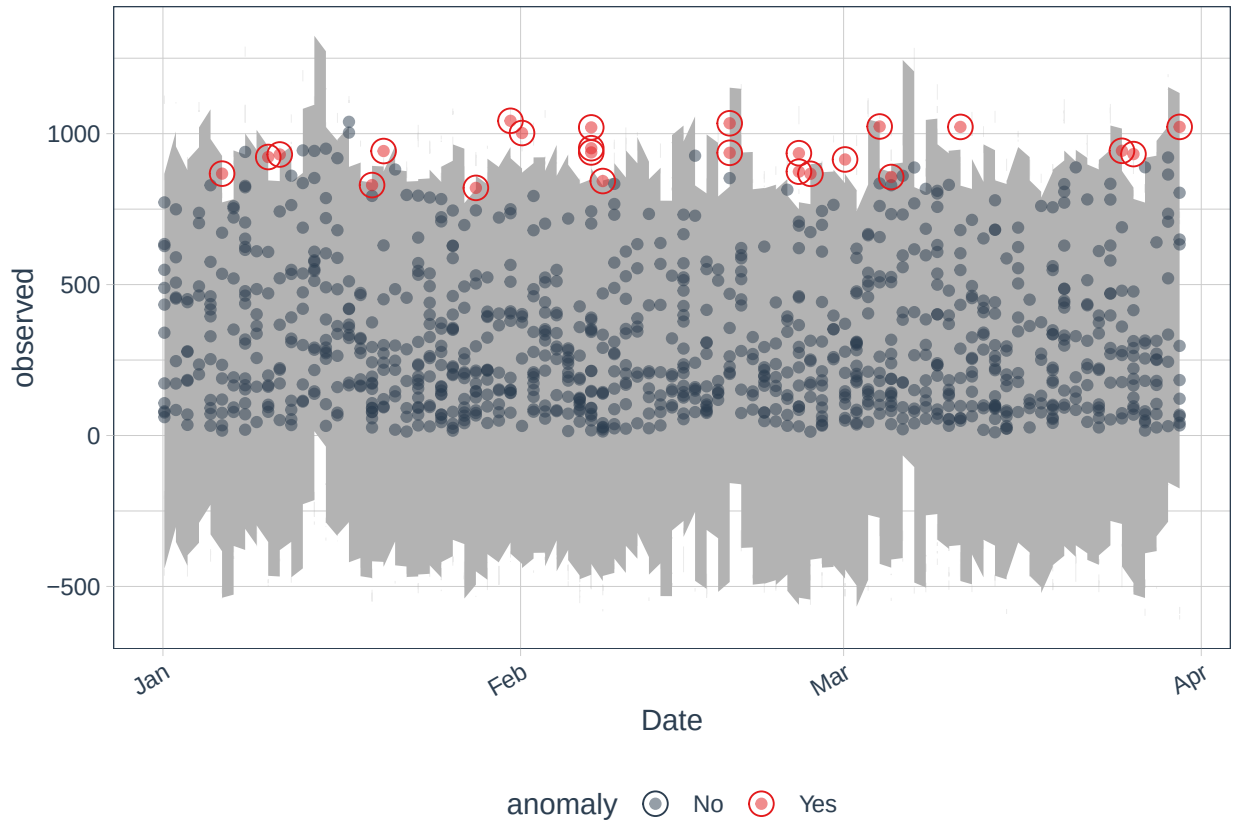
#Recomposition

```
df %>%
time_decompose(Sales, method = 'stl', frequency = 'auto', trend = 'auto') %>%
anomalize(remainder, method = 'gesd', alpha = 0.1, max_anoms = 0.1) %>%
time_recompose() %>%
plot_anomalies(time_recomposed = TRUE, ncol = 3, alpha_dots = 0.5)
```

```
## Converting from tbl_df to tbl_time.
## Auto-index message: index = Date

## frequency = 11 seconds

## trend = 11 seconds
```




```
anomalies = df %>%
time_decompose(Sales, method = 'stl', frequency = 'auto', trend = 'auto') %>%
anomalize(remainder, method = 'gesd', alpha = 0.05, max_anoms = 0.1) %>%
time_recompose() %>%
filter(anomaly == 'Yes')
```

```
## Converting from tbl_df to tbl_time.
## Auto-index message: index = Date

## frequency = 11 seconds

## trend = 11 seconds
```

Displaying tHE Anomalies

```
anomalies
```

```
## # A time tibble: 20 x 10
## # Index: Date
##    Date                observed season trend remainder remainder_l1 remainder_l2
##    <dttm>                 <dbl>  <dbl> <dbl>     <dbl>        <dbl>        <dbl>
##  1 2019-01-06 03:00:00     868. -37.1  223.       682.        -699.         670.
##  2 2019-01-10 03:00:00     923.  12.4  181.       729.        -699.         670.
```

```
##  3 2019-01-19 03:00:00     830. -37.1  168.       699.        -699.         670.
##  4 2019-01-20 03:00:00     942. -25.2  261.       707.        -699.         670.
##  5 2019-01-28 03:00:00     820. -38.0  174.       684.        -699.         670.
##  6 2019-01-31 03:00:00    1043.  -9.34 276.       776.        -699.         670.
##  7 2019-02-01 03:00:00    1002. -37.1  269.       771.        -699.         670.
##  8 2019-02-07 03:00:00    1021.  12.5  197.       811.        -699.         670.
##  9 2019-02-07 03:00:00     952. -25.2  186.       791.        -699.         670.
## 10 2019-02-07 03:00:00     938. -38.0  211.       765.        -699.         670.
## 11 2019-02-19 03:00:00    1034. -18.9  204.       849.        -699.         670.
## 12 2019-02-25 03:00:00     935. -38.0  194.       779.        -699.         670.
## 13 2019-02-25 03:00:00     874. -18.9  182.       711.        -699.         670.
## 14 2019-02-26 03:00:00     867. -25.2  135.       757.        -699.         670.
## 15 2019-03-01 03:00:00     915.  14.8  201.       698.        -699.         670.
## 16 2019-03-04 03:00:00    1024. -38.0  387.       675.        -699.         670.
## 17 2019-03-05 03:00:00     856. -38.0  171.       724.        -699.         670.
## 18 2019-03-11 03:00:00    1022. -25.2  217.       831.        -699.         670.
## 19 2019-03-26 03:00:00     932.  22.1  170.       740.        -699.         670.
## 20 2019-03-30 03:00:00    1022. -38.0   98.8      962.        -699.         670.
## # ... with 3 more variables: anomaly <chr>, recomposed_l1 <dbl>,
## #   recomposed_l2 <dbl>
```

Conclusion

Carrefour should investigate the anomalies that were in the months of February and March since this is where we have several Anomalies.