Part 3

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Part 3: Association Rules

Specifying the Question

- Create association rules that will allow you to identify relationships between variables in the dataset.
- Provide insights for your analysis.

```
# Load Package
library(arules)
```

```
## Loading required package: Matrix
```

```
##
## Attaching package: 'arules'
```

```
## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

Reading the Data

```
# Load Dataset
path <- "http://bit.ly/SupermarketDatasetII"
trans<-read.transactions(path, sep = ",")
```

```
## Warning in asMethod(object): removing duplicated items in transactions
```

```
trans
```

```
## transactions in sparse format with
##  7501 transactions (rows) and
##  119 items (columns)
```

Checking the Data

```r
# check info on the data
trans
```

```
## transactions in sparse format with
##  7501 transactions (rows) and
##  119 items (columns)
```

```r
# verifying the object class
class(trans)
```

```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

```r
# Previewing our first 5 transactions
inspect(trans[1:5])
```

```
##     items
## [1] {almonds,
##      antioxydant juice,
##      avocado,
##      cottage cheese,
##      energy drink,
##      frozen smoothie,
##      green grapes,
##      green tea,
##      honey,
##      low fat yogurt,
##      mineral water,
##      olive oil,
##      salad,
##      salmon,
##      shrimp,
##      spinach,
##      tomato juice,
##      vegetables mix,
##      whole weat flour,
##      yams}
## [2] {burgers,
##      eggs,
##      meatballs}
## [3] {chutney}
## [4] {avocado,
##      turkey}
## [5] {energy bar,
##      green tea,
##      milk,
##      mineral water,
##      whole wheat rice}
```

```r
# preview the items that make up our dataset,
# alternatively we can do the following
# ---
#
items<-as.data.frame(itemLabels(trans))
colnames(items) <- "Item"
head(items, 10)
```

```
##                  Item
## 1             almonds
## 2  antioxydant juice
## 3           asparagus
## 4             avocado
## 5         babies food
## 6               bacon
## 7      barbecue sauce
## 8           black tea
## 9         blueberries
## 10         body spray
```

```r
# Generating a summary of the transaction dataset
# ---
# This would give us some information such as the most purchased items,
# distribution of the item sets (no. of items purchased in each transaction), etc.
summary(trans)
```

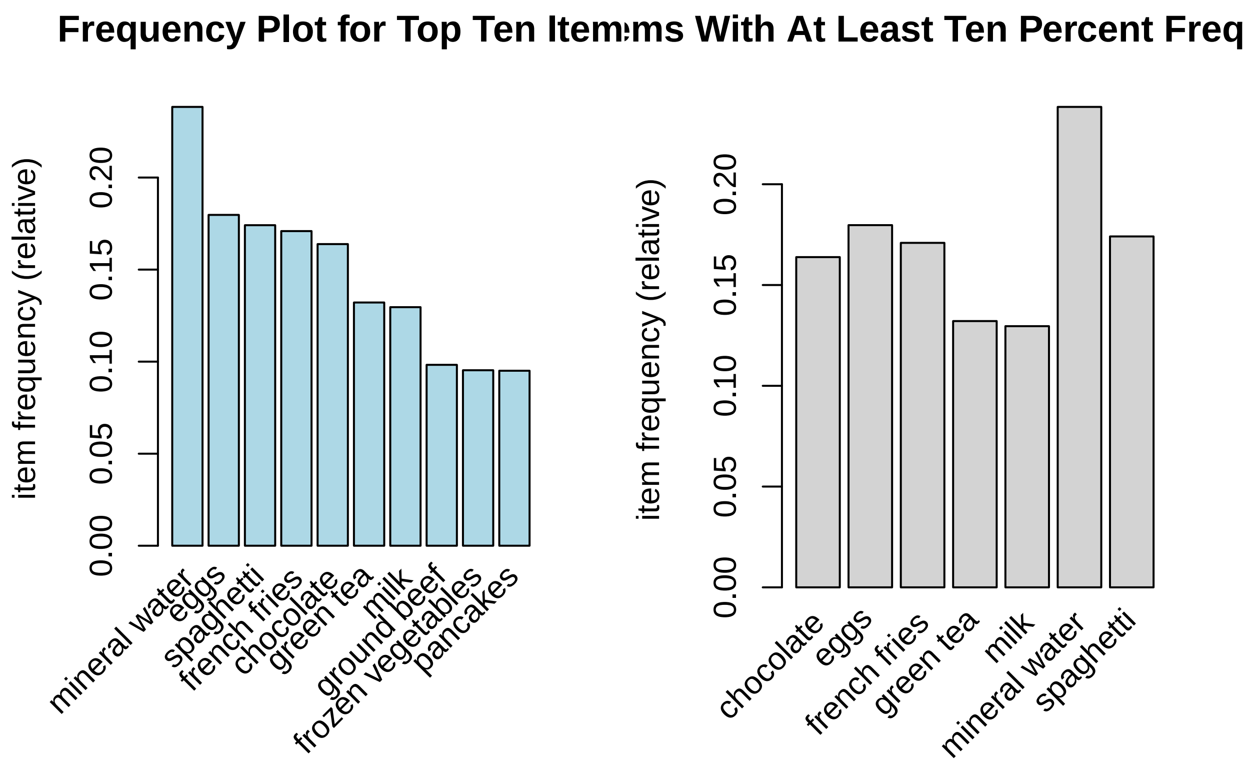
```
## transactions as itemMatrix in sparse format with
##  7501 rows (elements/itemsets/transactions) and
##  119 columns (items) and a density of 0.03288973
##
## most frequent items:
## mineral water          eggs     spaghetti  french fries     chocolate
##          1788          1348          1306          1282          1229
##       (Other)
##         22405
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 1754 1358 1044  816  667  493  391  324  259  139  102   67   40   22   17    4
##   18   19   20
##    1    2    1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   3.914   5.000  20.000
##
## includes extended item information - examples:
##              labels
## 1           almonds
## 2 antioxydant juice
## 3         asparagus
```

The top 5 most frequently bought items are mineral water, eggs, spaghetti, french fries and chocolate

```r
# Plot bar charts to visualize the frequencies of the most frequent items
# options(repr.plot.width = 15, repr.plot.height = 8)

par(mfrow = c(1, 2))

# plot the frequency of items
itemFrequencyPlot(trans, topN = 10,col="lightblue", main = "Frequency Plot for Top Ten Items")
itemFrequencyPlot(trans, support = 0.1,col="lightgray", main = "Items With At Least Ten Percent Frequen
```




```r
# find the 10 least popular items
least_items = itemFrequency(trans, type = "relative")
head(sort(least_items), 10)
```

```
##     water spray        napkins          cream        bramble            tea
##    0.0003999467   0.0006665778   0.0009332089   0.0018664178   0.0038661512
##         chutney mashed potato chocolate bread   dessert wine        ketchup
##    0.0041327823   0.0041327823   0.0042660979   0.0043994134   0.0043994134
```

The top 5 least frequently bought items are water spray, napkins, cream, bramble and tea

Building a Model

```r
# Building a model based on association rules
# We use Min Support as 0.001 and confidence as 0.8
rules <- apriori (trans, parameter = list(supp = 0.001, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.02s].
## writing ... [74 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```r
rules
```

```
## set of 74 rules
```

Using a confidence level of 0.80 and support of 0.001 we have a model with 74 rules. An increase in minimum support will result in a decrease in the number of rules by the model. However, a slight decrease in the confidence level will result in a huge increase in the rules created by the models.

```r
# Lets get more information on the rules formed
# More statistical information such as support, lift and confidence is also provided.
# ---
#
summary(rules)
```

```
## set of 74 rules
##
## rule length distribution (lhs + rhs):sizes
##  3  4  5  6
## 15 42 16  1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.000   4.000   4.000   4.041   4.000   6.000
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001067   Min.   :0.8000   Min.   :0.001067   Min.   : 3.356
##  1st Qu.:0.001067   1st Qu.:0.8000   1st Qu.:0.001333   1st Qu.: 3.432
##  Median :0.001133   Median :0.8333   Median :0.001333   Median : 3.795
##  Mean   :0.001256   Mean   :0.8504   Mean   :0.001479   Mean   : 4.823
##  3rd Qu.:0.001333   3rd Qu.:0.8889   3rd Qu.:0.001600   3rd Qu.: 4.877
##  Max.   :0.002533   Max.   :1.0000   Max.   :0.002666   Max.   :12.722
```

```
##      count
##  Min.   : 8.000
##  1st Qu.: 8.000
##  Median : 8.500
##  Mean   : 9.419
##  3rd Qu.:10.000
##  Max.   :19.000
##
## mining info:
##   data ntransactions support confidence
##  trans          7501   0.001        0.8
##                                                                      call
##  apriori(data = trans, parameter = list(supp = 0.001, conf = 0.8))
```

The set of 74 rules has a maximum rule length of 6 and a minimum of 3.

```
# lets take a peek at the first 5 rules of the associative model formed.
inspect(rules[1:10])
```

```
##      lhs                                rhs             support     confidence
## [1]  {frozen smoothie, spinach}    => {mineral water} 0.001066524 0.8888889
## [2]  {bacon, pancakes}             => {spaghetti}     0.001733102 0.8125000
## [3]  {nonfat milk, turkey}         => {mineral water} 0.001199840 0.8181818
## [4]  {ground beef, nonfat milk}    => {mineral water} 0.001599787 0.8571429
## [5]  {mushroom cream sauce, pasta} => {escalope}      0.002532996 0.9500000
## [6]  {milk, pasta}                 => {shrimp}        0.001599787 0.8571429
## [7]  {cooking oil, fromage blanc}  => {mineral water} 0.001199840 0.8181818
## [8]  {black tea, salmon}           => {mineral water} 0.001066524 0.8000000
## [9]  {black tea, frozen smoothie}  => {milk}          0.001199840 0.8181818
## [10] {red wine, tomato sauce}      => {chocolate}     0.001066524 0.8000000
##      coverage    lift      count
## [1]  0.001199840  3.729058  8
## [2]  0.002133049  4.666587 13
## [3]  0.001466471  3.432428  9
## [4]  0.001866418  3.595877 12
## [5]  0.002666311 11.976387 19
## [6]  0.001866418 11.995203 12
## [7]  0.001466471  3.432428  9
## [8]  0.001333156  3.356152  8
## [9]  0.001466471  6.313973  9
## [10] 0.001333156  4.882669  8
```

The interpretation of this will require the understanding of several words. - Support -> How popular an itemset is, as measured by the proportion of transactions in which an itemset appears. - Confidence -> How often one item A appears whenever another item B appears in a transaction. This is usually a conditional probability. - Lift -> A rule with a lift of > 1 it would imply that those two occurrences are dependent on one another and useful for predicting.

Thus in the 5th rule with a confidence level ~ 0.95 means that it is very likely that these three items are bought together by every customer.

The results reveal that the model is 95% confident that aperson buying mushroom cream sauce and pasta will buy escalope, 75% confident that a person buying milk and pasta will buy shrimp, etc,.

```r
# So lets sort the rules by the conficence levels to see the items are mostly bought together
rules<-sort(rules, by="confidence", decreasing=TRUE)
inspect(rules[1:10])
```

```
##      lhs                        rhs                 support confidence    coverage      lift count
## [1]  {french fries,
##       mushroom cream sauce,
##       pasta}                 => {escalope}      0.001066524  1.0000000 0.001066524 12.606723     8
## [2]  {ground beef,
##       light cream,
##       olive oil}             => {mineral water} 0.001199840  1.0000000 0.001199840  4.195190     9
## [3]  {cake,
##       meatballs,
##       mineral water}         => {milk}          0.001066524  1.0000000 0.001066524  7.717078     8
## [4]  {cake,
##       olive oil,
##       shrimp}                => {mineral water} 0.001199840  1.0000000 0.001199840  4.195190     9
## [5]  {mushroom cream sauce,
##       pasta}                 => {escalope}      0.002532996  0.9500000 0.002666311 11.976387    19
## [6]  {red wine,
##       soup}                  => {mineral water} 0.001866418  0.9333333 0.001999733  3.915511    14
## [7]  {eggs,
##       mineral water,
##       pasta}                 => {shrimp}        0.001333156  0.9090909 0.001466471 12.722185    10
## [8]  {herb & pepper,
##       mineral water,
##       rice}                  => {ground beef}   0.001333156  0.9090909 0.001466471  9.252498    10
## [9]  {ground beef,
##       pancakes,
##       whole wheat rice}      => {mineral water} 0.001333156  0.9090909 0.001466471  3.813809    10
## [10] {frozen vegetables,
##       milk,
##       spaghetti,
##       turkey}                => {mineral water} 0.001199840  0.9000000 0.001333156  3.775671     9
```

The following rules with a confidence level of 1 means that the items are almost always bought in that combination. Therefore, the marketing division would have to find a way to create promotions on these items.

There are 4 rules with 100% confidence

For instance, a promotion campaign would be like buy french fries and get 50 percent off on Mushroom cream sauce.

```r
# If we're interested in making a promotion relating to the sale of shrimp,
# we could create a subset of rules concerning these products
# This would tell us the items that the customers bought before purchasing shrimp

# If we wanted to determine the items that customers buying shrimps might buy

# Subset the rules
shrimp <- subset(rules, subset = lhs %pin% "shrimp")

# Order by confidence
```

```r
shrimp<-sort(shrimp, by="confidence", decreasing=TRUE)

# inspect top 5
inspect(shrimp[1:5])
```

```
##     lhs                        rhs                 support confidence    coverage     lift count
## [1] {cake,
##      olive oil,
##      shrimp}               => {mineral water} 0.001199840  1.0000000 0.001199840 4.195190     9
## [2] {chocolate,
##      frozen vegetables,
##      olive oil,
##      shrimp}               => {mineral water} 0.001199840  0.9000000 0.001333156 3.775671     9
## [3] {light cream,
##      mineral water,
##      shrimp}               => {spaghetti}     0.001066524  0.8888889 0.001199840 5.105326     8
## [4] {ground beef,
##      salmon,
##      shrimp}               => {spaghetti}     0.001066524  0.8888889 0.001199840 5.105326     8
## [5] {escalope,
##      french fries,
##      shrimp}               => {chocolate}     0.001066524  0.8888889 0.001199840 5.425188     8
```

Recommendations Shrimps could be bundled up with cake, olive oil, or with light cream, mineral water, etc, during the promotion season

Part 4: Anomaly Detection

Specifying the Question

- Check whether there are any anomalies in the given sales dataset. The objective of this task being fraud detection.

```r
# Load tidyverse and anomalize
# ---
#
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.2 --
## v ggplot2 3.3.6     v purrr   0.3.4
## v tibble  3.1.7     v dplyr   1.0.9
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x tidyr::expand() masks Matrix::expand()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## x tidyr::pack()   masks Matrix::pack()
## x dplyr::recode() masks arules::recode()
## x tidyr::unpack() masks Matrix::unpack()
```

```
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(tibbletime)
```

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

```
library(timetk)
```

```
# load data and convert it to as_tbl_time
anom <- read.csv('http://bit.ly/CarreFourSalesDataset')
head(anom)
```

```
##        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
```

First we have to format the Date column as date attribute.

```
# conversion to date
anom$Date <- as.Date(anom$Date , format = "%m/%d/%y")
head(anom)
```

```
##         Date    Sales
## 1 2020-01-05 548.9715
## 2 2020-03-08  80.2200
## 3 2020-03-03 340.5255
## 4 2020-01-27 489.0480
## 5 2020-02-08 634.3785
## 6 2020-03-25 627.6165
```

```
# Check dimensionality of the data
dim(anom)
```

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

There are 1000 rows and 2 columns in the dataset

```r
# Check for duplicates in the dataset
anyDuplicated(anom)
```

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

There are no duplicates in the dataset

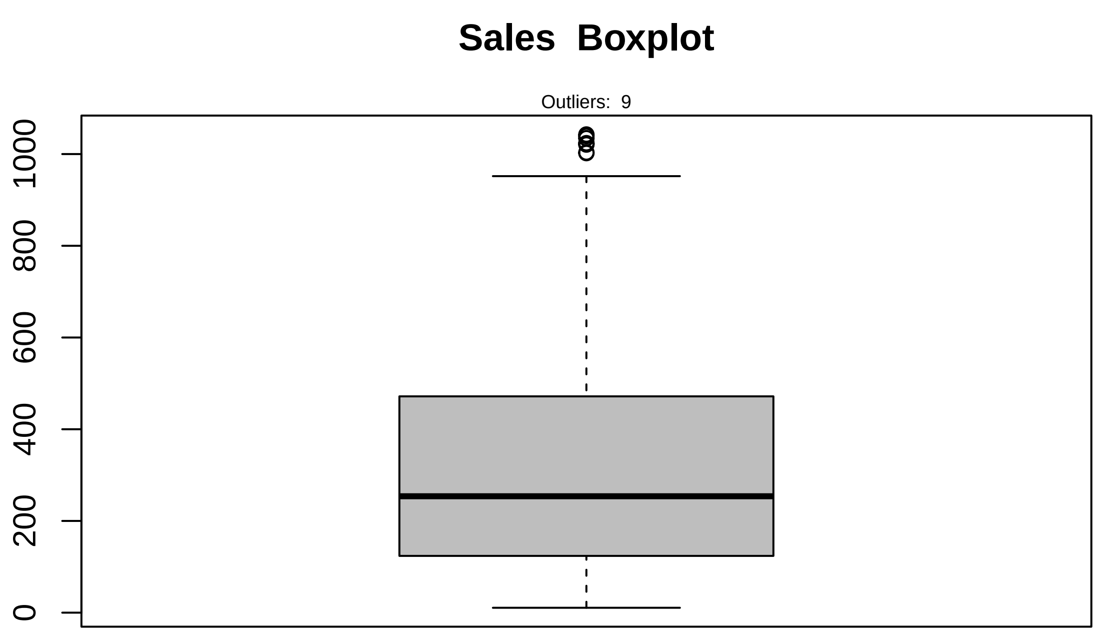
```r
# Check for missing values
colSums(is.na(anom))
```

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

There are no missing values in the dataset

```r
# Plotting boxplots to check for outliers
boxplot(anom$Sales,col='grey', main = 'Sales  Boxplot')

# display the number of outlier values in the column
outlier_sales <- boxplot.stats(anom$Sales)$out
mtext(paste("Outliers: ", paste(length(outlier_sales), collapse=", ")), cex=0.6)
```



There are 9 outliers. We will not be dropping the outliers because they represent actual goods sold

```r
# check for anomalies in the 'branch' column by scrutinizing its unique values
print(unique(anom$Date))
```

```
##  [1] "2020-01-05" "2020-03-08" "2020-03-03" "2020-01-27" "2020-02-08"
##  [6] "2020-03-25" "2020-02-25" "2020-02-24" "2020-01-10" "2020-02-20"
## [11] "2020-02-06" "2020-03-09" "2020-02-12" "2020-02-07" "2020-03-29"
## [16] "2020-01-15" "2020-03-11" "2020-01-01" "2020-01-21" "2020-03-05"
## [21] "2020-03-15" "2020-02-17" "2020-03-02" "2020-03-22" "2020-03-10"
## [26] "2020-01-25" "2020-01-28" "2020-01-07" "2020-03-23" "2020-01-17"
## [31] "2020-02-02" "2020-03-04" "2020-03-16" "2020-02-27" "2020-02-10"
## [36] "2020-03-19" "2020-02-03" "2020-03-07" "2020-02-28" "2020-03-27"
## [41] "2020-01-20" "2020-03-12" "2020-02-15" "2020-03-06" "2020-02-14"
## [46] "2020-03-13" "2020-01-24" "2020-01-06" "2020-02-11" "2020-01-22"
## [51] "2020-01-13" "2020-01-09" "2020-01-12" "2020-01-26" "2020-01-23"
## [56] "2020-02-23" "2020-01-02" "2020-02-09" "2020-03-26" "2020-03-01"
## [61] "2020-02-01" "2020-03-28" "2020-03-24" "2020-02-05" "2020-01-19"
## [66] "2020-01-16" "2020-01-08" "2020-02-18" "2020-01-18" "2020-02-16"
## [71] "2020-02-22" "2020-01-29" "2020-01-04" "2020-03-30" "2020-01-30"
## [76] "2020-01-03" "2020-03-21" "2020-02-13" "2020-01-14" "2020-03-18"
## [81] "2020-03-20" "2020-02-21" "2020-01-31" "2020-01-11" "2020-02-26"
## [86] "2020-03-17" "2020-03-14" "2020-02-04" "2020-02-19"
```

There are no anomalies in the date column

Univariate Analysis

```r
# identify numerical variables in the data1frame
nums <- unlist(lapply(anom, is.numeric))

# create a subset that contains the numerical variables
numerics <- subset(anom, select=nums)
```

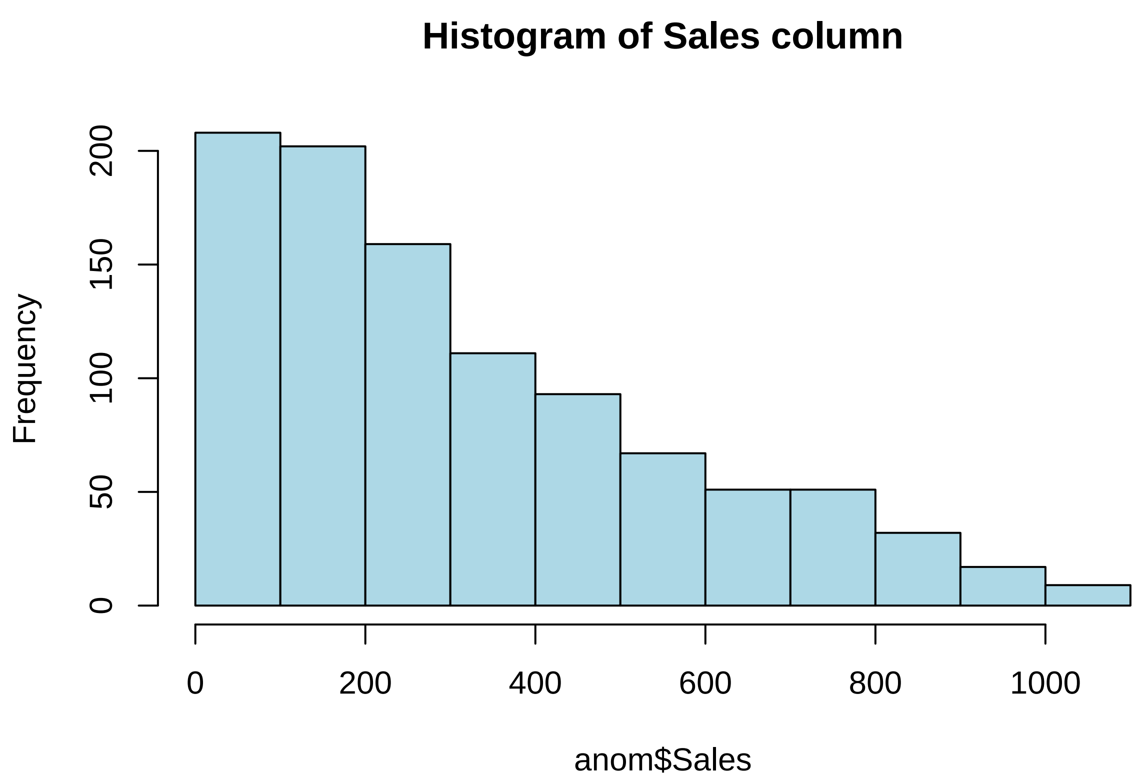
```r
# compute the measures of cenral tendancy and the measures of dispersion of the numerical variables and
library(moments)

statistics <- data.frame(
  Mean = apply(numerics, 2, mean),
  Median = apply(numerics, 2, median),
  Min = apply(numerics, 2, min),
  Max = apply(numerics, 2, max),
  Variance= apply(numerics, 2, var),
  Std = apply(numerics, 2, sd),
  Skewness = apply(numerics, 2, skewness),
  Kurtosis = apply(numerics, 2, kurtosis))

# round off the values to 2 decimal places and display the data1frame
statistics <- round(statistics, 2)
statistics
```

```
##         Mean Median   Min     Max Variance    Std Skewness Kurtosis
## Sales 322.97 253.85 10.68 1042.65  60459.6 245.89     0.89     2.91
```

```r
hist(anom$Sales, main = 'Histogram of Sales column',col="lightblue")
```



The data is left skewed and as the amount of sales increases the amount of goods bought reduces

```r
# Check the range of dates of our dataset
paste(c('Earliest:'), min(anom$Date))
```

```
## [1] "Earliest: 2020-01-01"
```

```r
paste(c('Latest:'), max(anom$Date))
```

```
## [1] "Latest: 2020-03-30"
```

The dataset has data from January 1st 2020 to March 30th 2020. So three months of data.

```r
# Check the range of Sales of our dataset
paste(c('Earliest:'), min(anom$Sales))
```

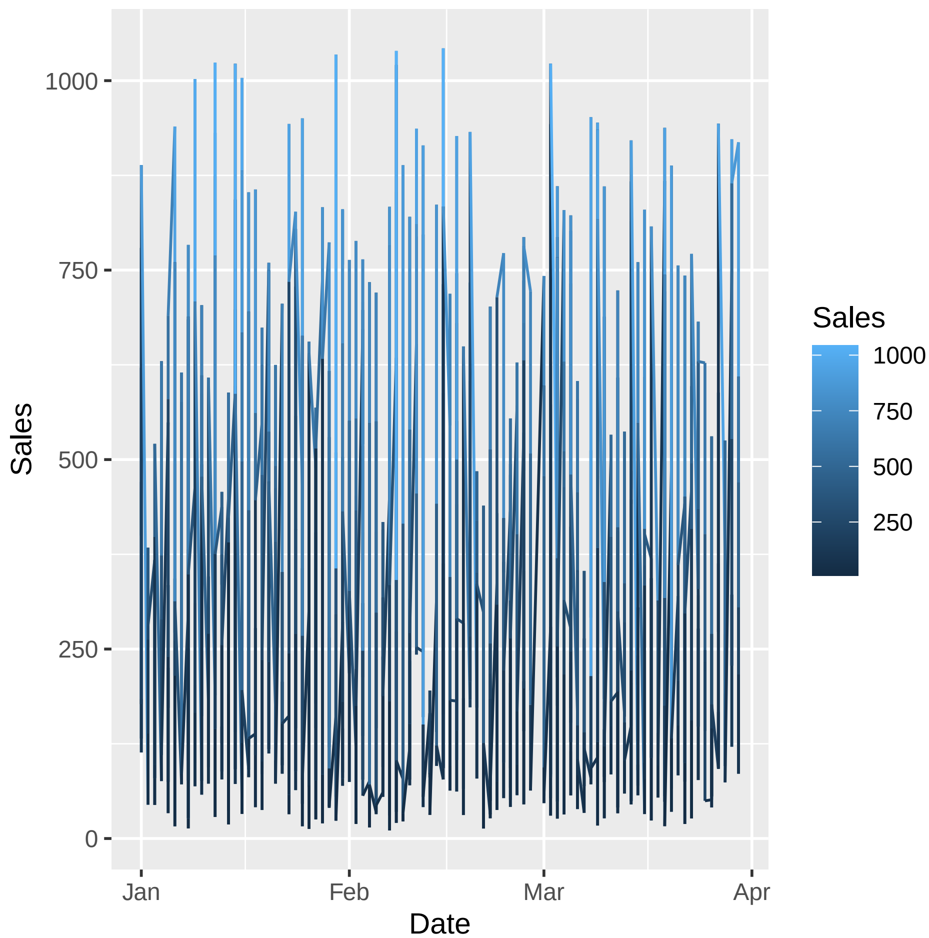
```
## [1] "Earliest: 10.6785"
```

```r
paste(c('Latest:'), max(anom$Sales))
```

```
## [1] "Latest: 1042.65"
```

The minimum sales is 10.67 and the maximum sale is 1042.65

```
#Plotting the data
library(ggplot2)
ggplot(anom, aes(x=Date, y=Sales, color=Sales)) + geom_line()
```



Anomaly Detection

First lets convert the df to a different format.

```
# # sort the table in ascending order of 'date'
# anom  = anom[order(anom$Date),]
#
# # convert dataset to tibble
# anomX <- as_tbl_time(anom, Date)
# class(anomX)
# plot (anomX)
```

```
# install.packages("devtools")
# devtools::install_github("twitter/AnomalyDetection")
# library(AnomalyDetection)
```

```r
# Convert the data into Tibble and  Convert to a Tibble, message=TRUE
sales_ts = anom %>%
  as_tibble() %>%
  as_tbl_time(Date) %>%
  arrange(Date) %>%
  as_period("daily")
```

```r
library(anomalize)
sales_anomaly <- sales_ts %>%
  time_decompose(Sales) %>%
  anomalize(remainder,max_anoms = 0.2, alpha=0.05) %>%
  time_recompose() %>% glimpse()
```

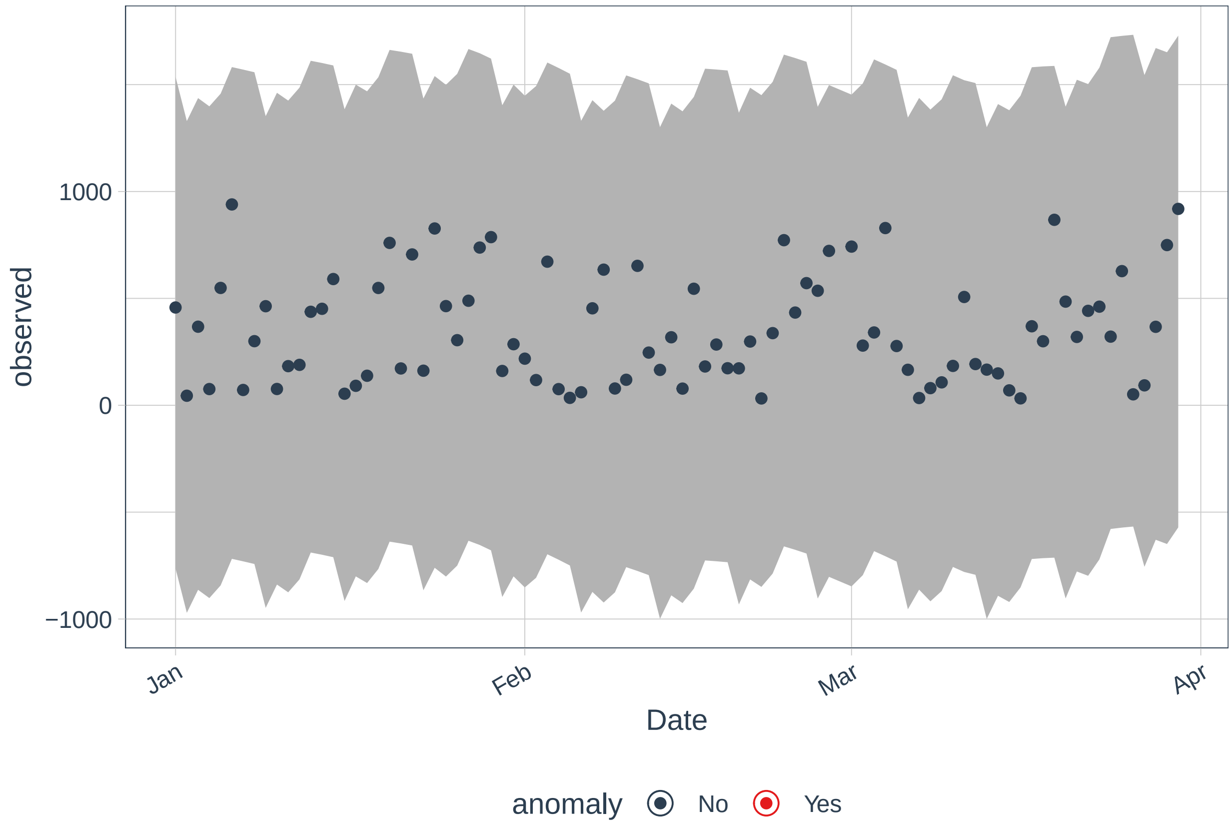
```
## frequency = 7 days
```

```
## trend = 30 days
```

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

```
## Rows: 89
## Columns: 10
## $ Date          <date> 2020-01-01, 2020-01-02, 2020-01-03, 2020-01-04, 2020-01~
## $ observed      <dbl> 457.4430, 44.5935, 367.5525, 75.7785, 548.9715, 939.5400~
## $ season        <dbl> 71.60220, -137.93561, -32.93877, -73.88690, -17.91742, 1~
## $ trend         <dbl> 296.3521, 298.8125, 301.2728, 303.7331, 307.0337, 310.33~
## $ remainder     <dbl> 89.488658, -116.283358, 99.218460, -154.067738, 259.8551~
## $ remainder_l1  <dbl> -1131.823, -1131.823, -1131.823, -1131.823, -1131.823, -~
## $ remainder_l2  <dbl> 1168.64, 1168.64, 1168.64, 1168.64, 1168.64, 1168.64, 11~
## $ anomaly       <chr> "No", "No", "No", "No", "No", "No", "No", "No", "No", "N~
## $ recomposed_l1 <dbl> -763.8688, -970.9462, -863.4891, -901.9769, -842.7068, -~
## $ recomposed_l2 <dbl> 1536.594, 1329.517, 1436.974, 1398.486, 1457.756, 1582.0~
```

```r
# Plot
sales_anomaly %>% plot_anomalies(time_recomposed = TRUE)
```



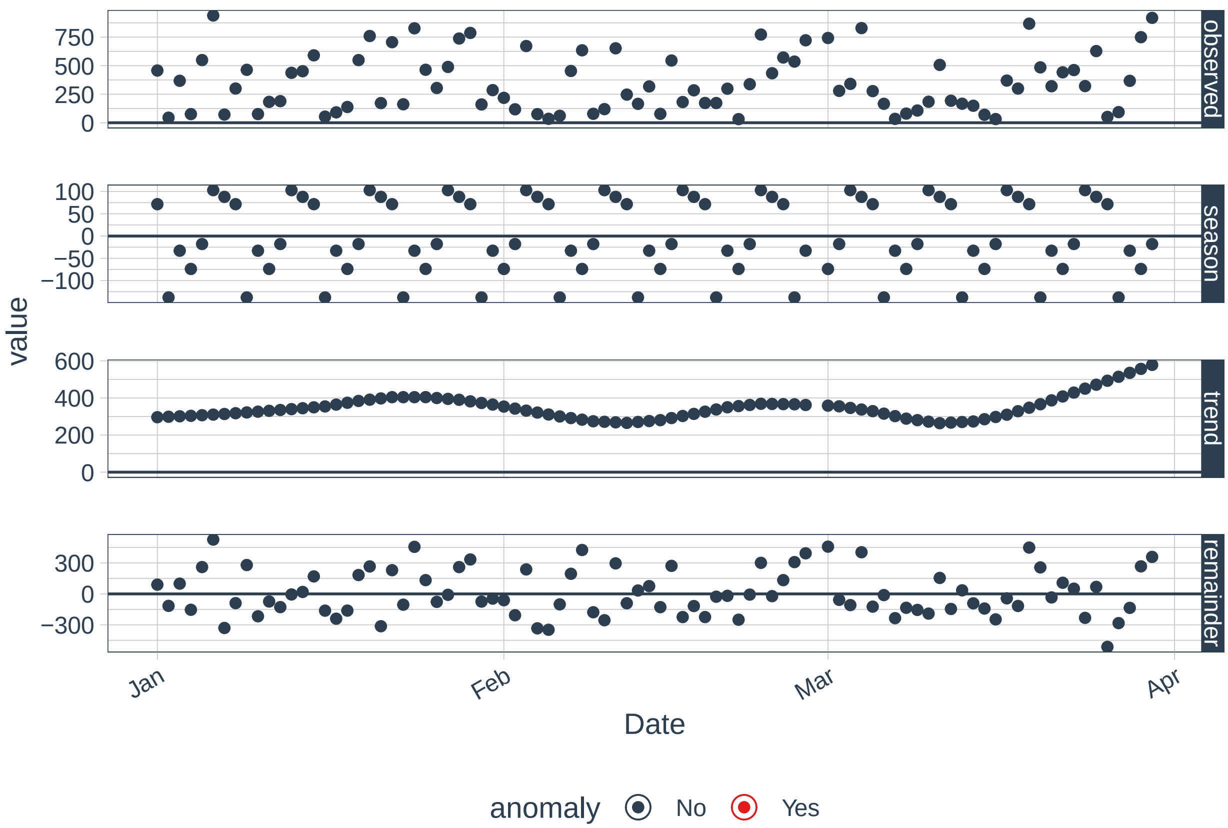

```
#sales_anomaly %>% plot_anomaly_decomposition(time_recompose = T)
```

There is are no Anomalies in our Sales Data

```
# Checking for trend
sales_ts %>%
  time_decompose(Sales, method = "stl",  frequency = "auto", trend = "auto") %>%
  anomalize(remainder, method = "gesd", alpha = 0.05, max_anoms = 0.1) %>%
  plot_anomaly_decomposition()
```

```
## frequency = 7 days
```

```
## trend = 30 days
```



There are no anomalies in our data set

Conclusion

There are no anomalies in our data