Anomaly_Detection

Group B

20/02/2021

Abstract

Anomaly detection or Outlier detection identifies data points, events or observations that deviate from dataset's normal behavior. Anomalous data indicate critical incidents or potential opportunities. In order to take advantage of opportunities or fix costly problems anomaly detection has to be done in real time. Unsupervised machine learning models can be used to automate anomaly detection. Unsupervised anomaly detection algorithms scores data based on intrinsic properties of the dataset. Distances and densities are used to give an estimation what is normal and what is an outlier. Anomaly detection monitor is a tool developed for an online retailer to check product quality issues like profit opportunities and sales glitches. The application is built using R and Shinyapp following CRISP-DM framework.

Business Case

Objectives

Detect point anomalies from superstore dataset using K-NN and clustering methods

Import data

```r
#load libraries
library(readxl)
library(tidyr)
library(dplyr)
library(ggplot2)
library(anomalize)
library(lemon)
library(DMwR)
#library(CORElearn)
library(outForest)
library(factoextra)
```

```r
#read data from file
superstore<-read_excel("superstore.xls")
```

Data Understanding

US Superstore dataset is sourced from US superstore dataset . The dataset have online orders for Superstores in U.S. from 2014-2018. Tableau community is the owner of the dataset. The dataset has 9994 records and 21 attributes.

```
data_superstore
```

Table 1: Dataset description

Attribute	Data Type	Description
Row ID	numeric	row number
Order ID	character	unique order number
Order Date	numeric	order placed date
Ship Date	numeric	order shipping date
Ship Mode	character	shipping mode of order
Customer ID	character	unique customer id for order
Customer Name	character	name of customer
Segment	character	section of product
Country	character	country based on order
City	character	city based on order
State	character	state based on order
Postal Code	numeric	pin code
Region	character	region based on order
Product ID	character	product id of product
Category	character	category of product
Sub-Category	character	sub-category of product
Product Name	character	name of product
Sales	numeric	selling price of product
Quantity	numeric	order quantity
Discount	numeric	discount on product
Profit	numeric	profit from product

Data Preparation

```
#name columns
names(superstore)<-c("rowid","orderid","order_date","ship_date","ship_mode","customer_id",
                     "customer_name","segment","country","city","state","postal_code",
                     "region","product_id","category","sub_category","product_name",
                     "sales_amt","quantity","discount","profit_amt")

#drop columns with redundant information
superstore[,c("rowid","customer_name","country")]<-NULL


#convert to date
superstore$order_date<-as.Date(superstore$order_date,format="%Y-%m-%d")
superstore$ship_date<-as.Date(superstore$ship_date,format="%Y-%m-%d")
```

Descriptive Analysis

Continous variables summary

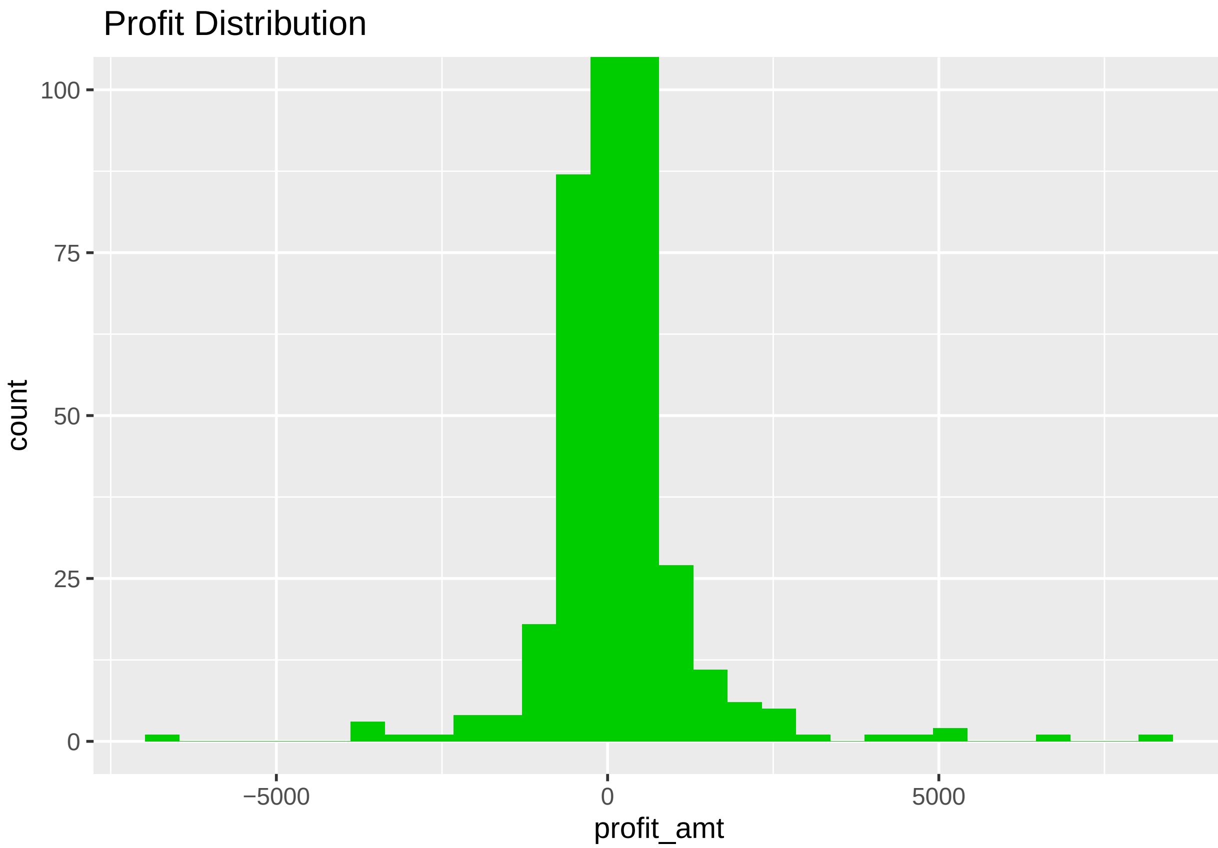
```r
superstore %>%
    select_if(is.numeric)%>%
    summary()
```

```
##   postal_code      sales_amt            quantity        discount
##  Min.   : 1040   Min.   :    0.444   Min.   : 1.00   Min.   :0.0000
##  1st Qu.:23223   1st Qu.:   17.280   1st Qu.: 2.00   1st Qu.:0.0000
##  Median :56431   Median :   54.490   Median : 3.00   Median :0.2000
##  Mean   :55190   Mean   :  229.858   Mean   : 3.79   Mean   :0.1562
##  3rd Qu.:90008   3rd Qu.:  209.940   3rd Qu.: 5.00   3rd Qu.:0.2000
##  Max.   :99301   Max.   :22638.480   Max.   :14.00   Max.   :0.8000
##    profit_amt
##  Min.   :-6599.978
##  1st Qu.:    1.729
##  Median :    8.666
##  Mean   :   28.657
##  3rd Qu.:   29.364
##  Max.   : 8399.976
```

Profit

```r
ggplot(data=superstore)+
  geom_histogram(mapping=aes(x=profit_amt),fill="green3")+
  coord_cartesian(ylim = c(0, 100))+
  labs(title=" Profit Distribution")
```

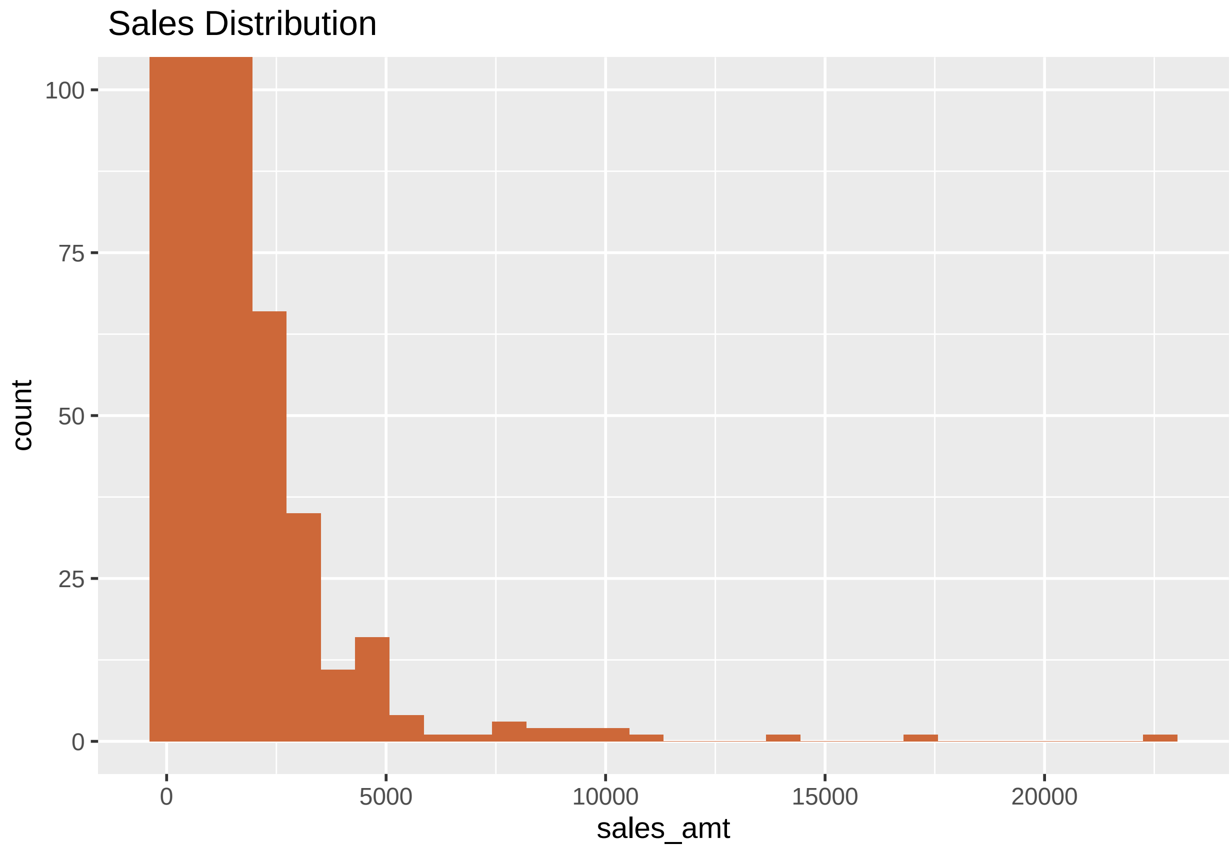
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Sales

```
ggplot(data=superstore)+
  geom_histogram(mapping=aes(x=sales_amt),fill="sienna3")+
  coord_cartesian(ylim = c(0, 100))+labs(title=" Sales Distribution")
```

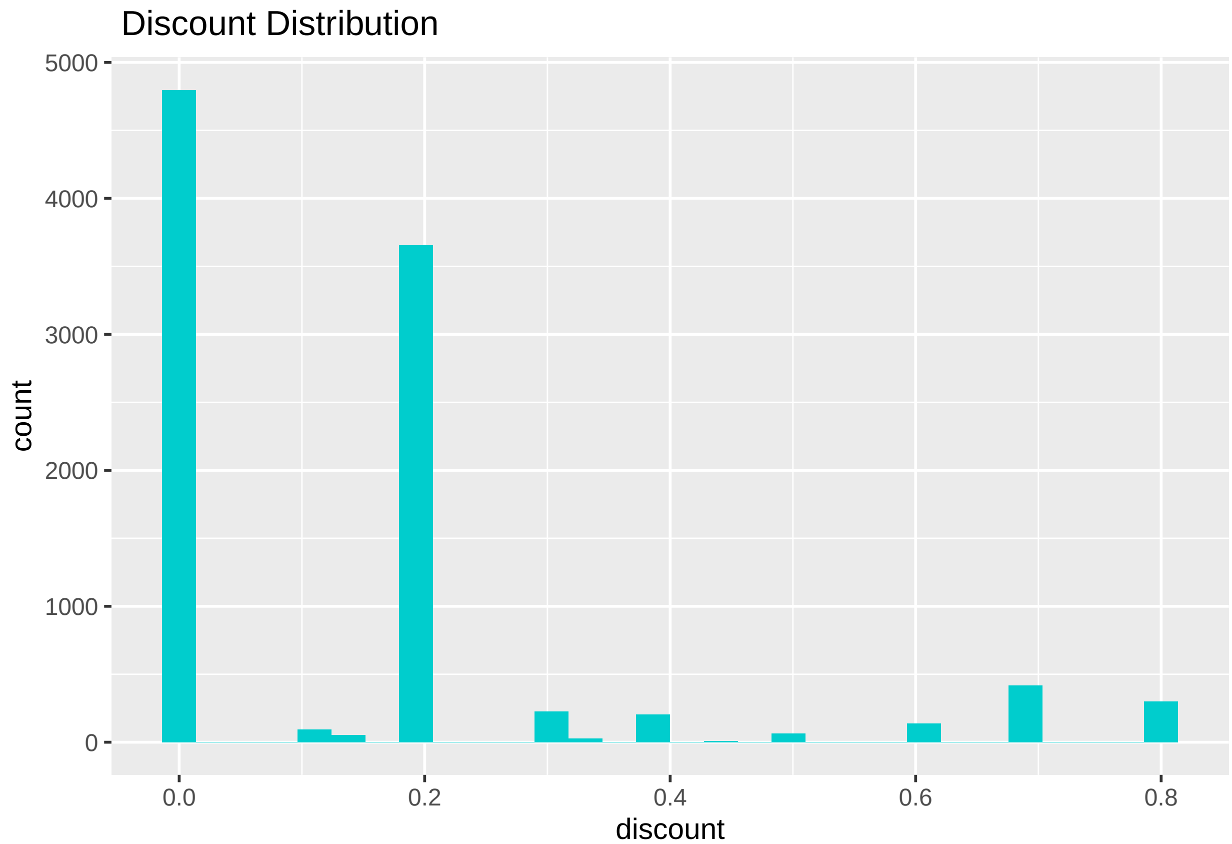
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Discount

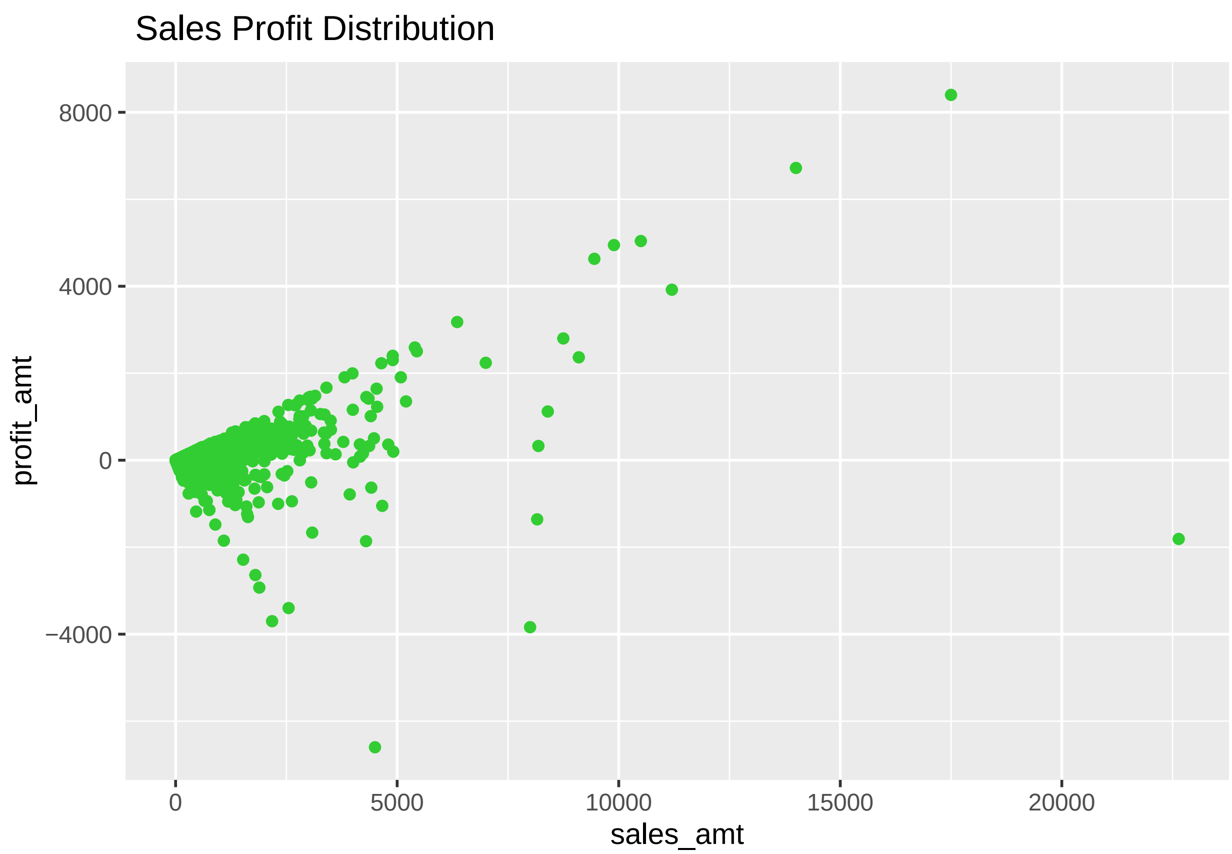
```
ggplot(data=superstore)+
  geom_histogram(mapping=aes(x=discount),fill="cyan3")+
  labs(title=" Discount Distribution")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



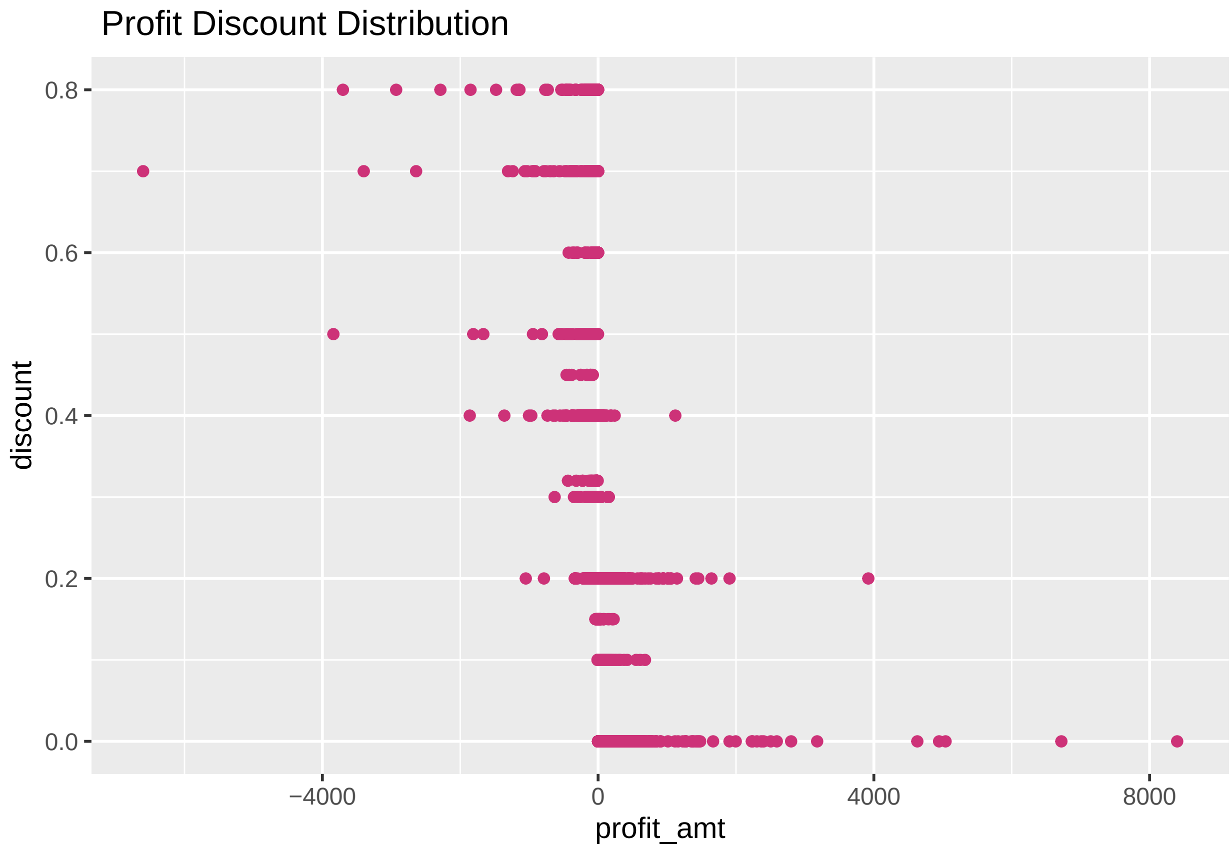
Sales Profit

```
ggplot(data = superstore) +
  geom_point(mapping = aes(x = sales_amt, y = profit_amt),colour="limegreen")+
  labs(title=" Sales Profit Distribution")
```



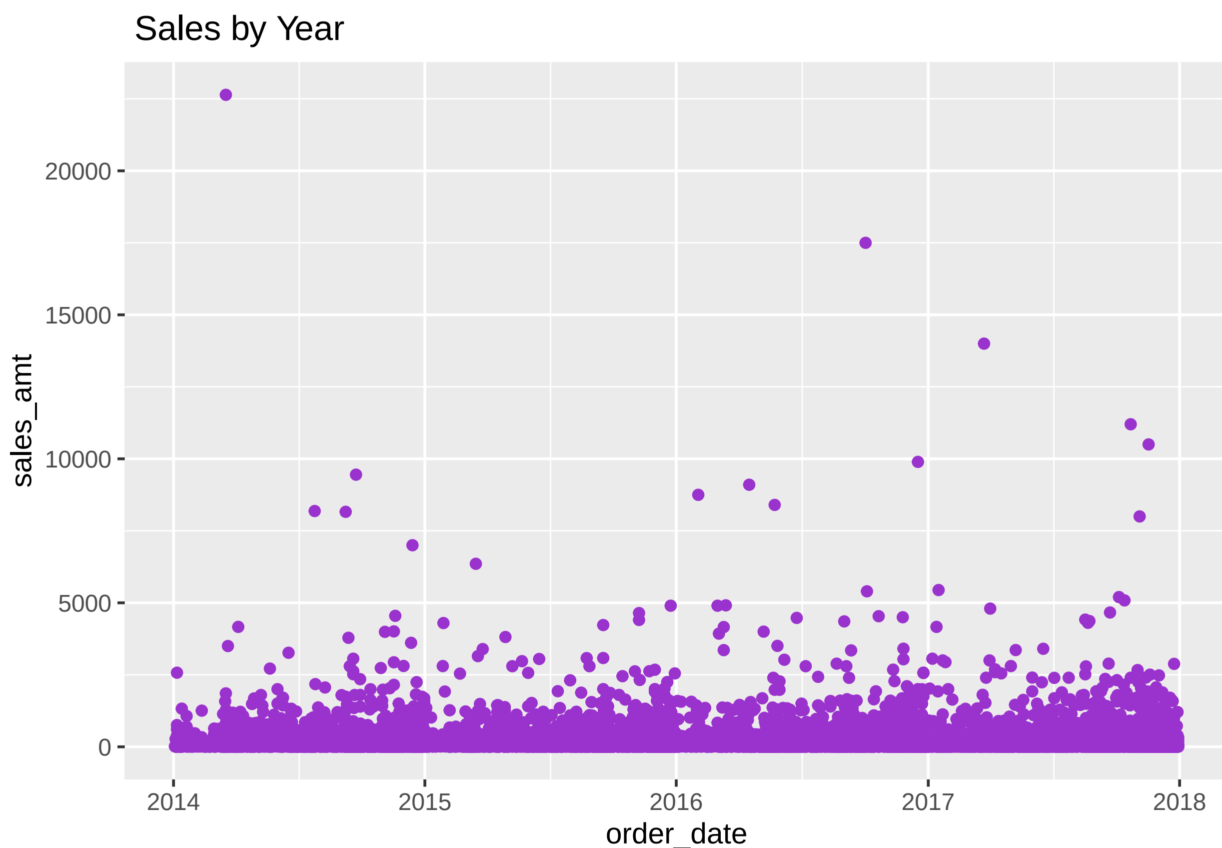
Profit Discount

```
ggplot(data = superstore) +
  geom_point(mapping = aes(x = profit_amt, y = discount),colour="violetred3")+
  labs(title=" Profit Discount Distribution")
```



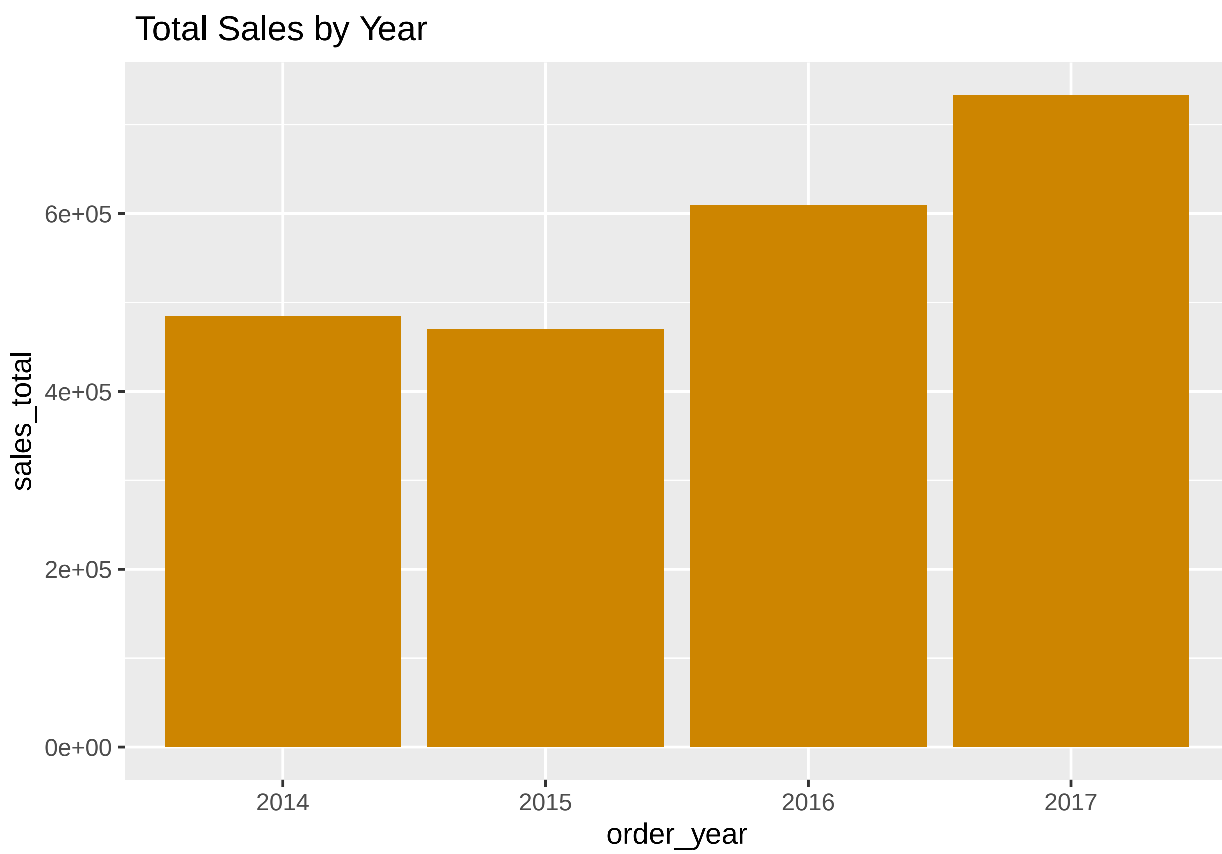
Sales by Year

```
ggplot(data=superstore,aes(x = order_date, y =sales_amt)) +
      geom_point(color = "darkorchid3") +
      labs(title=" Sales by Year")
```



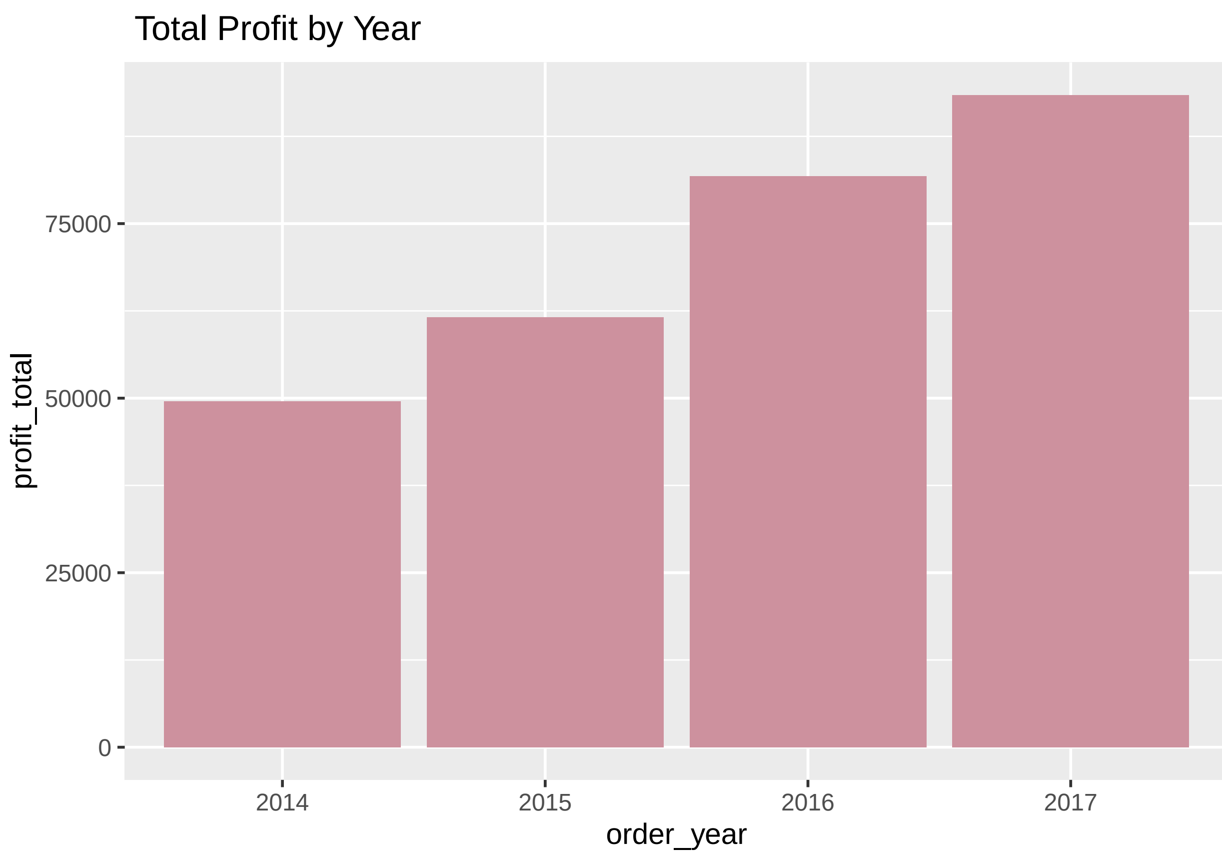
Total Sales by Year

```
sales_year<-aggregate(superstore$sales_amt,by=list(year=format(superstore$order_date, "%Y")),FUN=sum)
names(sales_year)<-c("order_year","sales_total")



ggplot(data=sales_year,aes(x = order_year, y =sales_total)) +
      geom_bar(stat="identity",fill = "orange3") +
      labs(title=" Total Sales by Year")
```



Profit by Year

```
profit_year<-aggregate(superstore$profit_amt,by=list(year=format(superstore$order_date, "%Y")),FUN=sum)
names(profit_year)<-c("order_year","profit_total")


ggplot(data=profit_year,aes(x = order_year, y =profit_total)) +
      geom_bar(stat="identity",fill = "pink3") +
      labs(title=" Total Profit by Year")
```




```r
# total product id
count_product_id<-unique(superstore$product_id)
length(count_product_id)
```

```
## [1] 1862
```

```r
#total product name
count_product_name<-unique(superstore$product_name)
length(count_product_name)
```

```
## [1] 1850
```

```r
#product name and product id mismatch
superstore %>%
  distinct(product_name,product_id) %>%
  group_by(product_id) %>%
  filter(n()>1) %>%
  select(product_id)
```

```
## # A tibble: 64 x 1
## # Groups:   product_id [32]
##    product_id
##    <chr>
##  1 FUR-FU-10004848
```

```
##   2 FUR-CH-10001146
##   3 OFF-BI-10004654
##   4 FUR-CH-10001146
##   5 OFF-PA-10002377
##   6 OFF-AR-10001149
##   7 OFF-PA-10000659
##   8 TEC-MA-10001148
##   9 FUR-FU-10004017
##  10 TEC-AC-10003832
## # ... with 54 more rows
```

```
#total category and subcategory

count_category<-unique(superstore$category)
length(count_category)
```

```
## [1] 3
```

```
count_subcategory<-unique(superstore$sub_category)
length(count_subcategory)
```

```
## [1] 17
```

```
superstore %>%
  distinct(category,sub_category)
```

```
## # A tibble: 17 x 2
##    category        sub_category
##    <chr>           <chr>
##  1 Furniture       Bookcases
##  2 Furniture       Chairs
##  3 Office Supplies Labels
##  4 Furniture       Tables
##  5 Office Supplies Storage
##  6 Furniture       Furnishings
##  7 Office Supplies Art
##  8 Technology      Phones
##  9 Office Supplies Binders
## 10 Office Supplies Appliances
## 11 Office Supplies Paper
## 12 Technology      Accessories
## 13 Office Supplies Envelopes
## 14 Office Supplies Fasteners
## 15 Office Supplies Supplies
## 16 Technology      Machines
## 17 Technology      Copiers
```

```
superstore_sales<-superstore %>%
                  select(order_date,sales_amt)


superstore_sales<-as_tibble(superstore_sales)
```

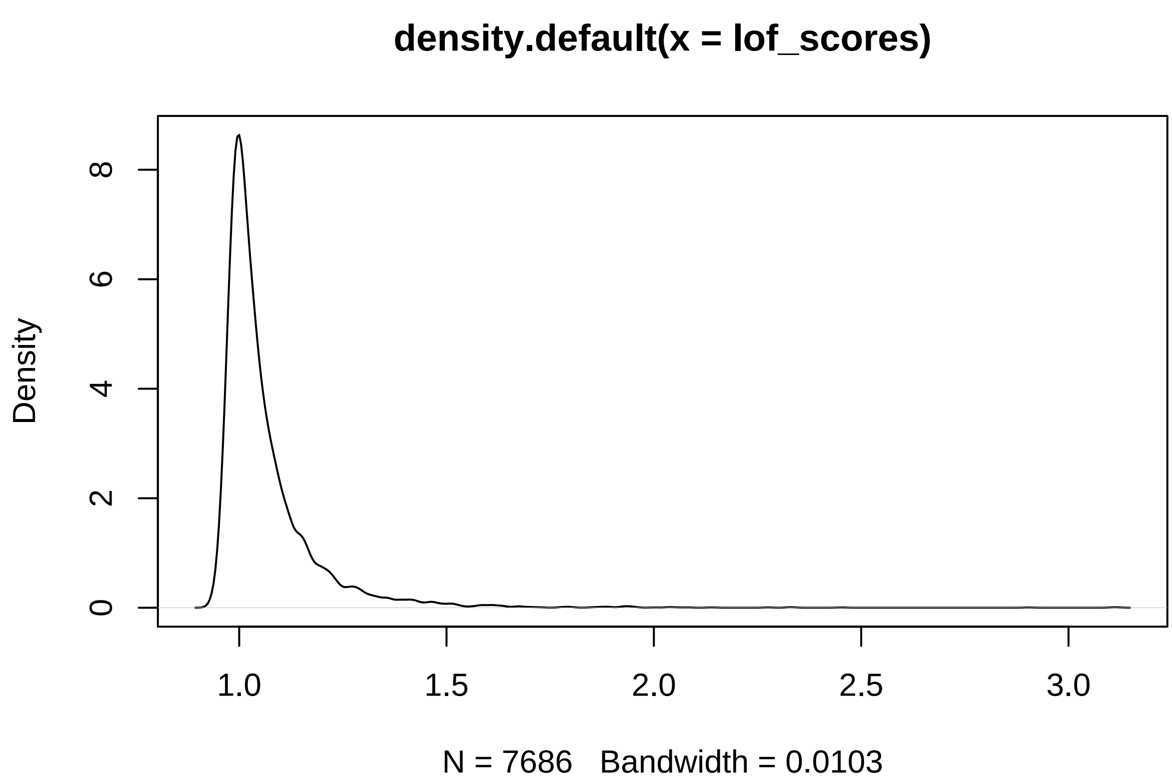
```
# superstore_sales_anomalized <- superstore_sales %>%
#     time_decompose(sales_amt, merge = TRUE) %>%
#     anomalize(remainder) %>%
#     time_recompose()
```

Model

Local Outlier Factor Algorithm -Nearest neighbour method

LOF uses density based methods to calculate degree of outlying.LOF is a unsupervised anomaly detection technique, evry point in the datase is assigned LOF score based on the threshold value it classify the datapoints as outlier or non-outlier.

```
#remove duplicates rows
superstore_unq<-superstore[!duplicated(superstore[c("sales_amt","profit_amt","quantity","discount")]),]

#select numerical variables
superstore_lof<-superstore_unq[,c("sales_amt","profit_amt","quantity","discount")]



 # for k=10
 lof_scores <- lofactor(superstore_lof, k=10)
 plot(density(lof_scores))
```



Manual Evaluation

```r
#top 5 outliers transactons
lof_outliers <- order(lof_scores >2, decreasing=T)[1:13]
superstore_unq[lof_outliers,]
```

```
## # A tibble: 13 x 18
##    orderid order_date ship_date  ship_mode customer_id segment city  state
##    <chr>   <date>     <date>     <chr>     <chr>       <chr>   <chr> <chr>
##  1 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  2 CA-201~ 2014-09-08 2014-09-12 Standard~ BM-11140    Consum~ San ~ Texas
##  3 US-201~ 2017-11-04 2017-11-04 Same Day  GT-14635    Corpor~ Burl~ Nort~
##  4 CA-201~ 2014-07-25 2014-07-27 Second C~ KL-16645    Consum~ San ~ Cali~
##  5 CA-201~ 2014-03-18 2014-03-23 Standard~ SM-20320    Home O~ Jack~ Flor~
##  6 CA-201~ 2017-04-17 2017-04-23 Standard~ SR-20425    Home O~ Loui~ Colo~
##  7 US-201~ 2017-12-07 2017-12-13 Standard~ HG-14965    Corpor~ Chic~ Illi~
##  8 CA-201~ 2016-01-04 2016-01-08 Standard~ BP-11185    Corpor~ Phil~ Penn~
##  9 CA-201~ 2015-09-06 2015-09-08 Second C~ AT-10435    Home O~ Tama~ Flor~
## 10 CA-201~ 2016-10-02 2016-10-09 Standard~ TC-20980    Corpor~ Lafa~ Indi~
## 11 CA-201~ 2016-11-25 2016-12-02 Standard~ CS-12505    Consum~ Lanc~ Ohio
## 12 US-201~ 2017-12-10 2017-12-13 First Cl~ WB-21850    Consum~ Phil~ Penn~
## 13 CA-201~ 2014-07-26 2014-07-30 Standard~ LF-17185    Consum~ San ~ Texas
## # ... with 10 more variables: postal_code <dbl>, region <chr>,
## #   product_id <chr>, category <chr>, sub_category <chr>, product_name <chr>,
## #   sales_amt <dbl>, quantity <dbl>, discount <dbl>, profit_amt <dbl>
```

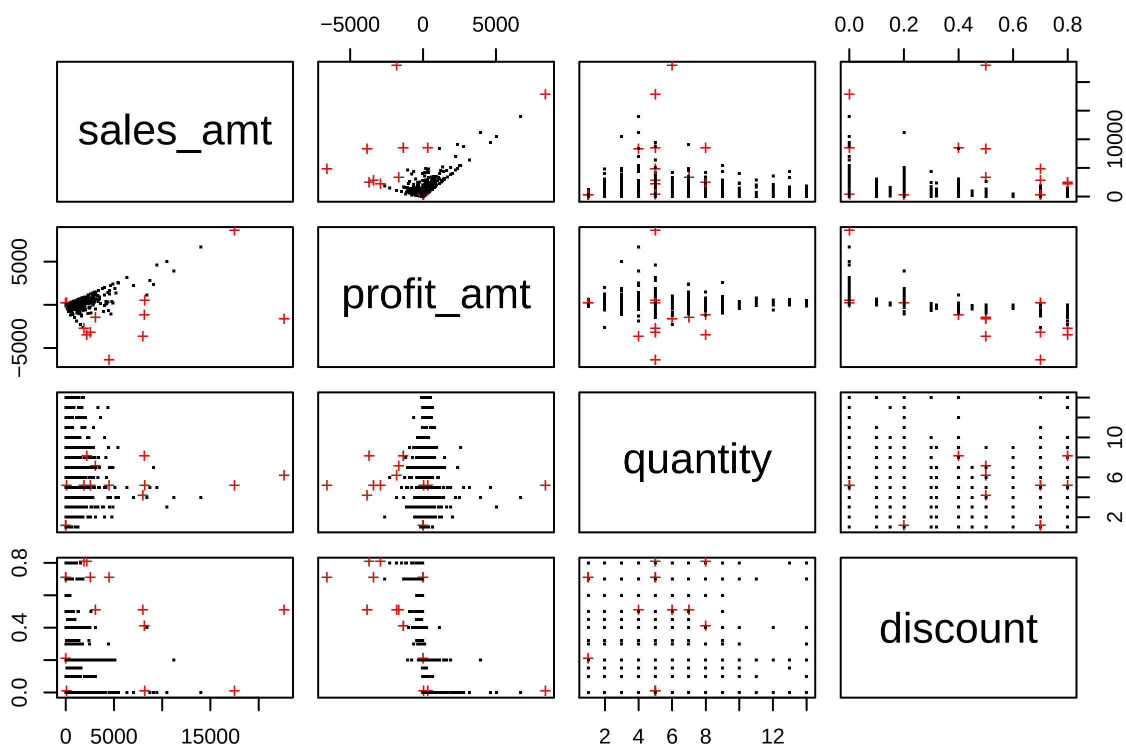
```r
#new column for outlier status

outlier_orderid<-superstore_unq[which(lof_scores >2),1]
vec<-as.vector(outlier_orderid$orderid)


superstore_unq<-mutate(superstore_unq,outlier_status=ifelse(orderid %in% (vec) ,"Yes","No"))

x<-subset(superstore_unq,superstore_unq$outlier_status=="Yes")
x
```

```
## # A tibble: 49 x 19
##    orderid order_date ship_date  ship_mode customer_id segment city  state
##    <chr>   <date>     <date>     <chr>     <chr>       <chr>   <chr> <chr>
##  1 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  2 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  3 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  4 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  5 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  6 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  7 US-201~ 2015-09-17 2015-09-21 Standard~ TB-21520    Consum~ Phil~ Penn~
##  8 CA-201~ 2014-09-08 2014-09-12 Standard~ BM-11140    Consum~ San ~ Texas
##  9 CA-201~ 2014-09-08 2014-09-12 Standard~ BM-11140    Consum~ San ~ Texas
## 10 CA-201~ 2014-09-08 2014-09-12 Standard~ BM-11140    Consum~ San ~ Texas
## # ... with 39 more rows, and 11 more variables: postal_code <dbl>,
## #   region <chr>, product_id <chr>, category <chr>, sub_category <chr>,
```

```
## #   product_name <chr>, sales_amt <dbl>, quantity <dbl>, discount <dbl>,
## #   profit_amt <dbl>, outlier_status <chr>
```

Plot LOF outliers

```
pch <- rep(".", 7000)
pch[lof_outliers] <- "+"
col <- rep("black",7000)
col[lof_outliers] <- "red"
pairs(superstore_lof, pch=pch, col=col)
```



Random Forest Algorithm

outForest is a random forest based implementation of the method. Each numeric variable is regressed onto all other variables using a random forest. If the scaled absolute difference between observed value and out-of-bag prediction is suspicioly large (e.g. more than three times the RMSE of the out-of-bag predictions), then a value is considered an outlier. After identification of outliers, they can be replaced e.g. by predictive mean matching from the non-outliers.

```
#dataframe for outforest
superstore_out<-superstore_unq[,c("sales_amt","profit_amt","quantity","discount")]
```

```r
#fit outforest
outforest_outlier<-outForest(superstore_out)
```

```
##
## Outlier identification by random forests
##
##   Variables to check:        sales_amt, profit_amt, quantity, discount
##   Variables used to check:   sales_amt, profit_amt, quantity, discount
##
##   Checking: sales_amt  profit_amt  quantity  discount
```

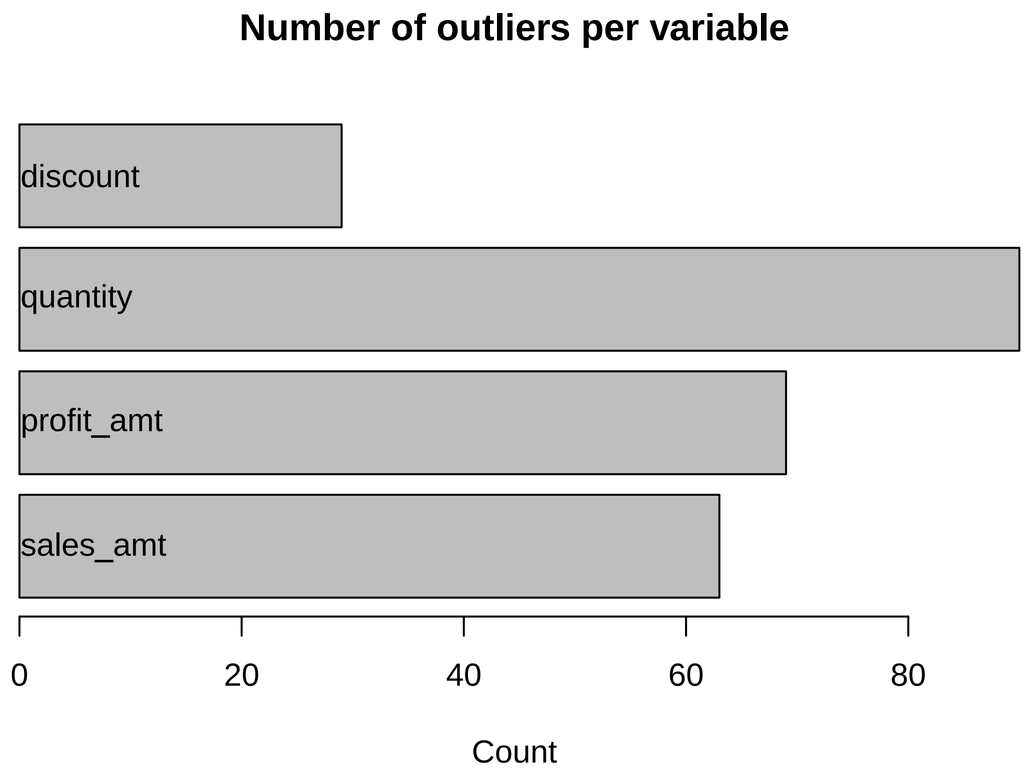
Manual Evaluation

Observed same set of top outliers as LOF algorithm

```r
#outlier rows, observed values, predicted and RMSE
head(outliers(outforest_outlier),13)
```

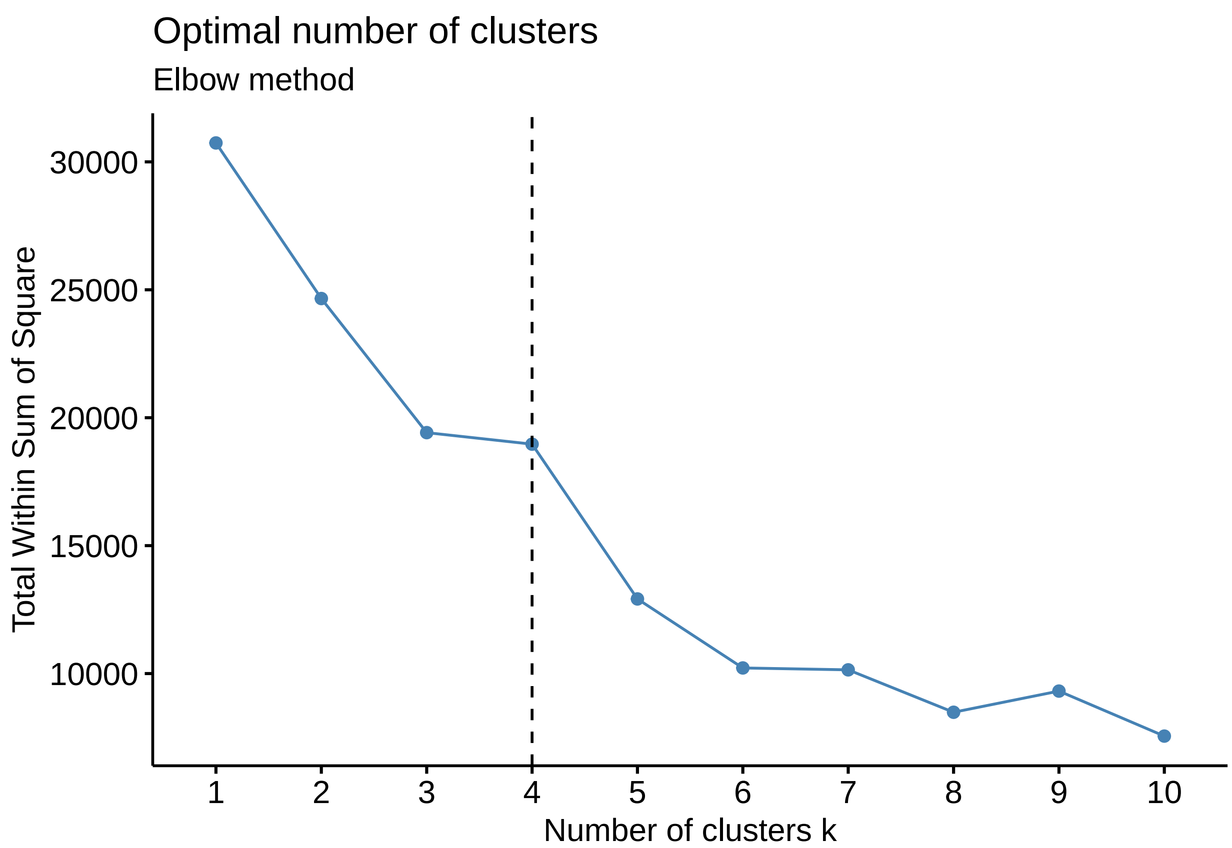
```
##      row        col  observed   predicted     rmse     score threshold
## 19  2452  sales_amt 22638.480  2282.47548 423.6672  48.04716         3
## 116 6269 profit_amt -6599.978 -1132.08929 168.8575 -32.38168         3
## 110 5613 profit_amt  8399.976  3159.34879 168.8575  31.03580         3
## 40  5613  sales_amt 17499.950  6413.03598 423.6672  26.16892         3
## 71   665 profit_amt -3839.990    92.25018 168.8575 -23.28733         3
## 119 6517 profit_amt  6719.981  3153.61314 168.8575  21.12058         3
## 81  2452 profit_amt -1811.078  1629.83797 168.8575 -20.37764         3
## 132 7555 profit_amt -3701.893  -880.84058 168.8575 -16.70671         3
## 49  6517  sales_amt 13999.960  6927.27302 423.6672  16.69397         3
## 16  2290  sales_amt  8187.650  1144.72605 423.6672  16.62372         3
## 2    164  sales_amt  8159.952  1643.28264 423.6672  15.38158         3
## 37  5324  sales_amt  8399.976  2322.40026 423.6672  14.34516         3
## 128 7089 profit_amt  4946.370  2543.50623 168.8575  14.23013         3
##     replacement
## 19    1999.9600
## 116  -1065.3720
## 110   2365.9818
## 40    4899.9300
## 71      70.1955
## 119   1351.9896
## 81     700.9800
## 132  -1065.3720
## 49    4899.9300
## 16     482.9400
## 2     1606.2300
## 37    1999.9600
## 128   1351.9896
```

```r
# Outliers per variable
plot(outforest_outlier)
```

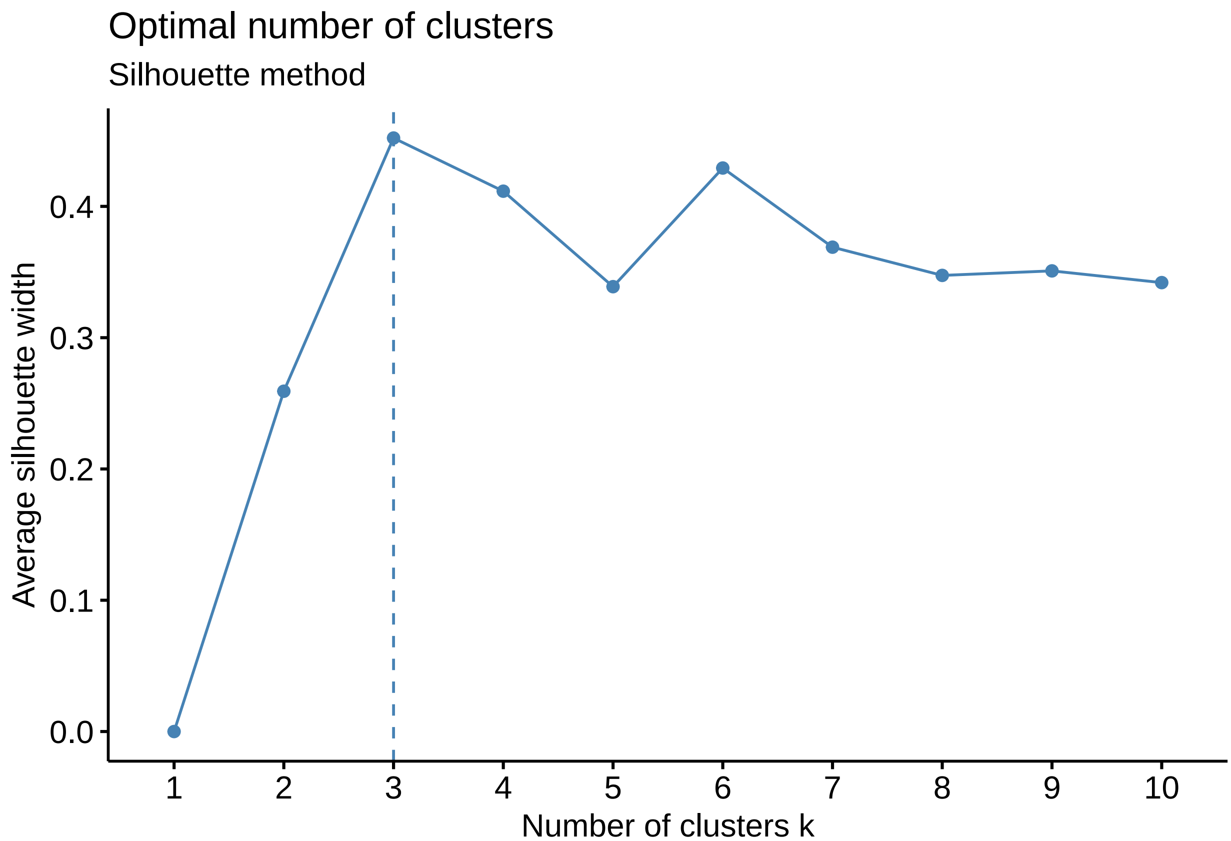


K Means Clustering

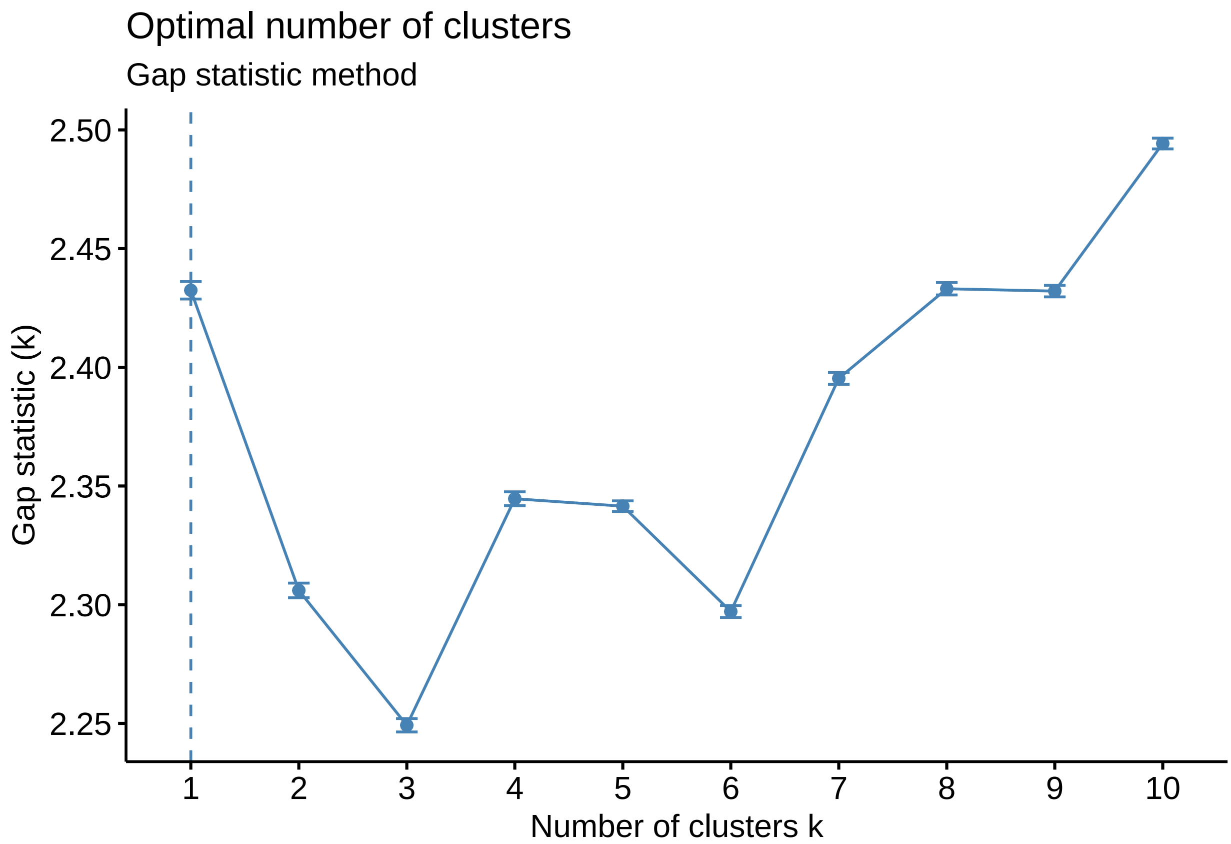
```
#find k value for clusters


superstore_kmean<-superstore_unq[,c("sales_amt","profit_amt","quantity","discount")]


# Elbow method
fviz_nbclust(scale(superstore_kmean), kmeans, method = c("wss"))+
  geom_vline(xintercept = 4, linetype = 2)+
  labs(subtitle = "Elbow method")
```



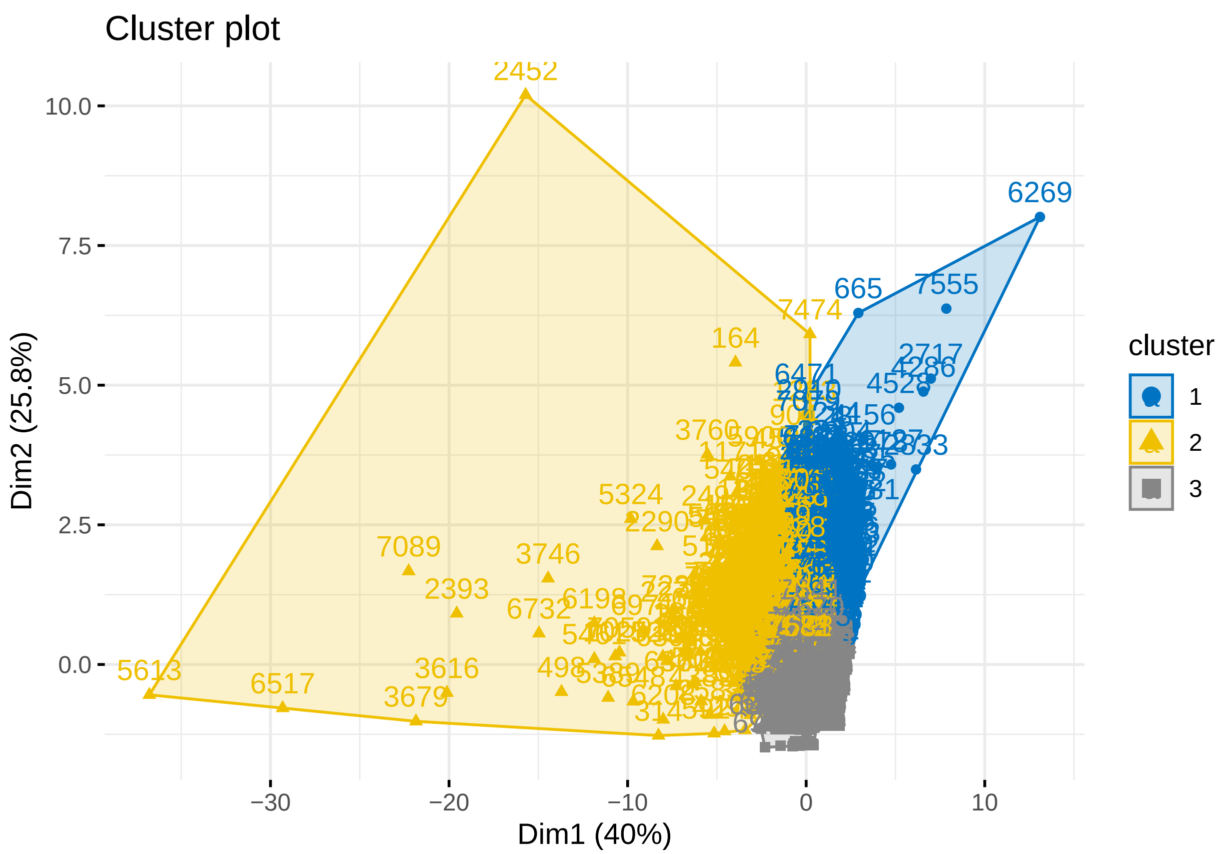

```
#Silhouette method

fviz_nbclust(scale(superstore_kmean), kmeans, method = "silhouette")+
  labs(subtitle = "Silhouette method")
```



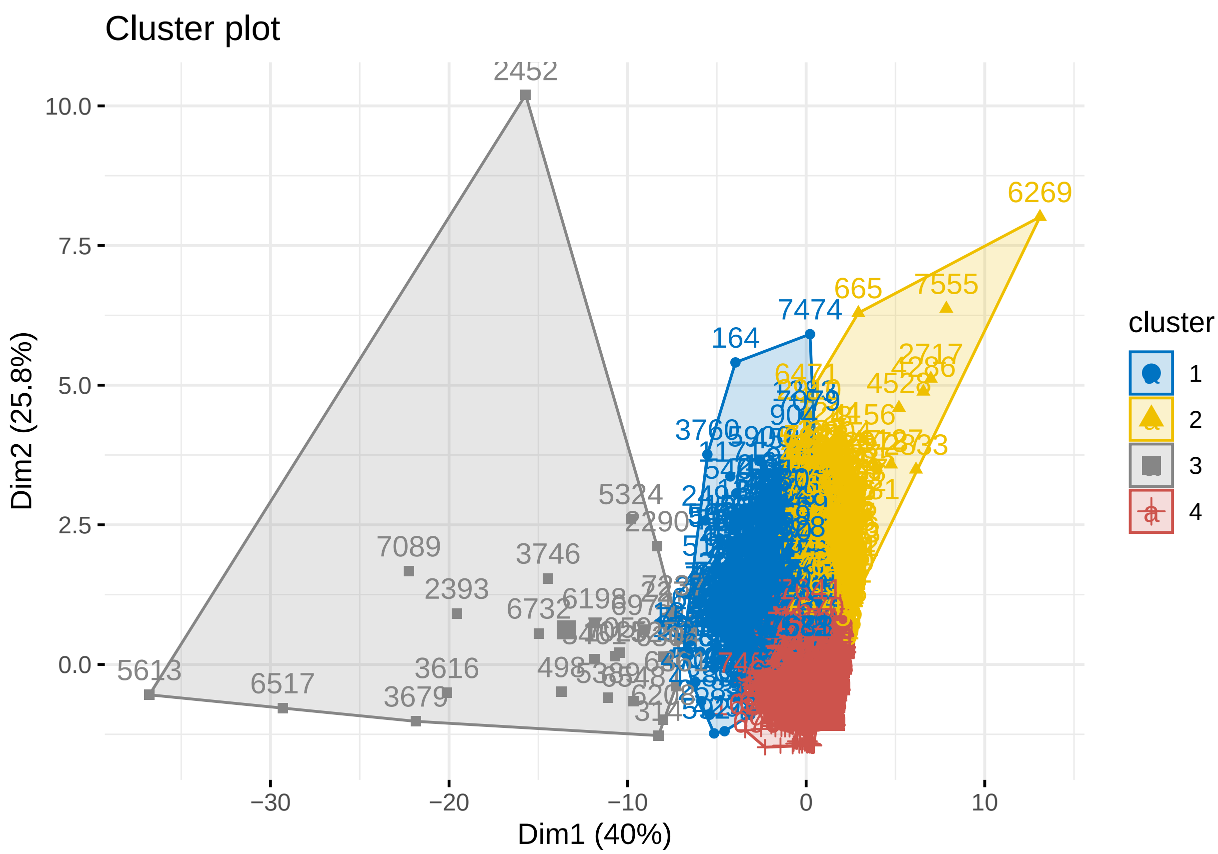

```
fviz_nbclust(scale(superstore_kmean), kmeans, nstart = 25,  method = "gap_stat", nboot = 50)+
  labs(subtitle = "Gap statistic method")
```




```
# clusters for k=3

km_clus<-kmeans(scale(superstore_kmean),3,nstart=25)

#Plot clusters
fviz_cluster(km_clus, data = superstore_kmean,palette = "jco",ggtheme = theme_minimal())
```




```
# clusters for k=4

km_clus<-kmeans(scale(superstore_kmean),4,nstart = 25)

#Plot clusters
fviz_cluster(km_clus, data = superstore_kmean,palette = "jco",ggtheme = theme_minimal())
```



Responsible ML Framework

Conclusion

Bibliography