ML 1000 Assignment 2

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To do list:

- Add Pie charts! by sub_category, region # (done)
- Create a Month variable to see the change of sales/profits by month?
- bar charts of profits/sales by region #(done)
- Output the characteristics of the orders with the highest and lowest profits/sales e.g. what made the order? when? bought what product? in which city/state/region? Any discount?
- relationship between discount & sales, discount & profits, sales & profits, and the role of region?
- from someone's analysis there is no significant change between the four discount categories when it comes to Sales
- sales/profits by month, rather than by date? color by region?

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

Objective

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

Data Understanding

US Superstore dataset is sourced from US uperstore 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.

Import data

```
superstore<- read_excel("US_Superstore_data.xls")</pre>
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L2236 / R2236C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L5276 / R5276C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L8800 / R8800C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9148 / R9148C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9149 / R9149C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9150 / R9150C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9388 / R9388C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9389 / R9389C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9390 / R9390C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9391 / R9391C12: '05408'
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9743 / R9743C12: '05408'
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

Attribute	Data Type	Description		
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		

```
## [1] "i..Row.ID-0 missing values"
                                         "Order.ID-0 missing values"
   [3] "Order.Date-0 missing values"
                                         "Ship.Date-0 missing values"
##
## [5] "Ship.Mode-0 missing values"
                                         "Customer.ID-0 missing values"
  [7] "Customer.Name-O missing values"
                                         "Segment-0 missing values"
  [9] "Country-O missing values"
                                         "City-O missing values"
##
## [11] "State-0 missing values"
                                         "Postal.Code-0 missing values"
## [13] "Region-0 missing values"
                                         "Product.ID-0 missing values"
## [15] "Category-O missing values"
                                         "Sub.Category-O missing values"
## [17] "Product.Name-0 missing values"
                                         "Sales-0 missing values"
## [19] "Quantity-0 missing values"
                                         "Discount-O missing values"
## [21] "Profit-0 missing values"
                                         "diff_in_days-0 missing values"
```

Get a general idea of the data set.

```
length(unique(data$Customer.ID))
```

[1] 793

```
#793 unique customer IDs
length(unique(data$Customer.Name))
```

[1] 793

```
#793 unique customer names - drop one of these two vars
length(unique(data$Order.Date))
```

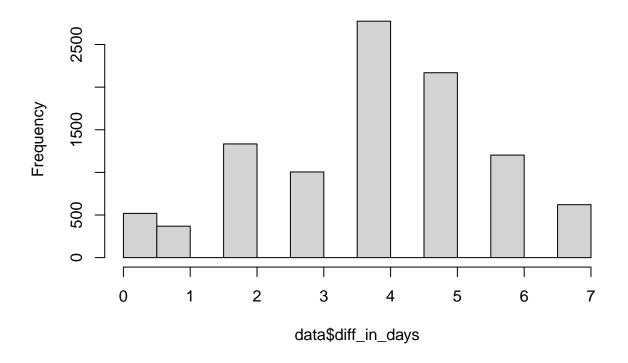
[1] 1237

```
#1237 unique order dates
length(unique(data$Ship.Date))
```

```
## [1] 1334
#1334 unique ship dates - more unique ship dates than order dates - orders made on the same day were sh
length(unique(data$Segment))
## [1] 3
unique(data$Segment)
## [1] "Consumer"
                     "Corporate" "Home Office"
#"Consumer" "Corporate" "Home Office"
unique(data$Country)
## [1] "United States"
#all are from US - could drop this variable due to no-variation introduced by it
length(unique(data$City))
## [1] 531
#531 different cities
length(unique(data$State))
## [1] 49
#49 states
length(unique(data$Postal.Code))
## [1] 631
#631 postal code - 793 unique customer IDs - some customers live very close!
unique(data$Region)
## [1] "South"
                 "West"
                           "Central" "East"
#only 4 regions
unique(data$Category)
## [1] "Furniture"
                         "Office Supplies" "Technology"
```

```
#only 3 categories - "Furniture" "Office Supplies" "Technology"
length(unique(data$Sub.Category))
## [1] 17
unique(data$Sub.Category)
## [1] "Bookcases"
                      "Chairs"
                                    "Labels"
                                                  "Tables"
                                                                "Storage"
## [6] "Furnishings" "Art"
                                    "Phones"
                                                                "Appliances"
                                                  "Binders"
                                                                "Supplies"
## [11] "Paper"
                      "Accessories" "Envelopes"
                                                  "Fasteners"
## [16] "Machines"
                     "Copiers"
#17 sub-categories
length(unique(data$Product.Name))
## [1] 1850
#1850 product names
length(unique(data$Product.ID))
## [1] 1862
#1862 product IDs - potential redundant variables!
hist(data$diff_in_days)
```

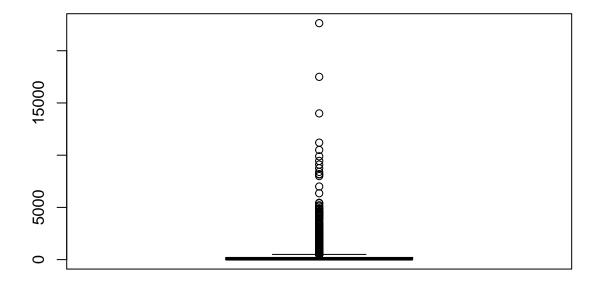
Histogram of data\$diff_in_days



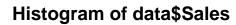
#The time difference between order date and ship date typically takes 4 days.
summary(data\$Sales)

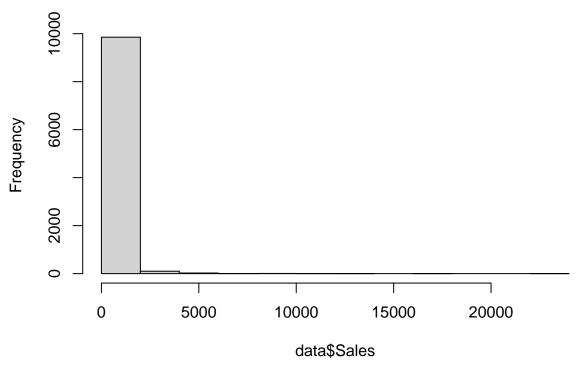
```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.444 17.280 54.490 229.858 209.940 22638.480
```

boxplot(data\$Sales)



hist(data\$Sales)

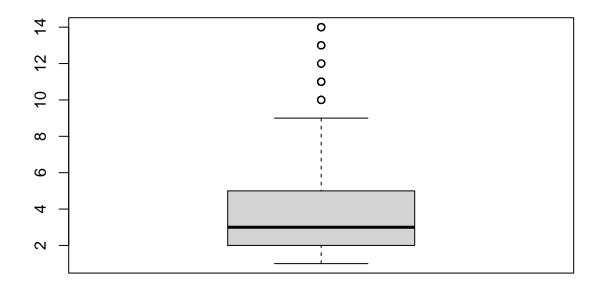




```
#a large amount of orders with very small Sales!
summary(data$Quantity)

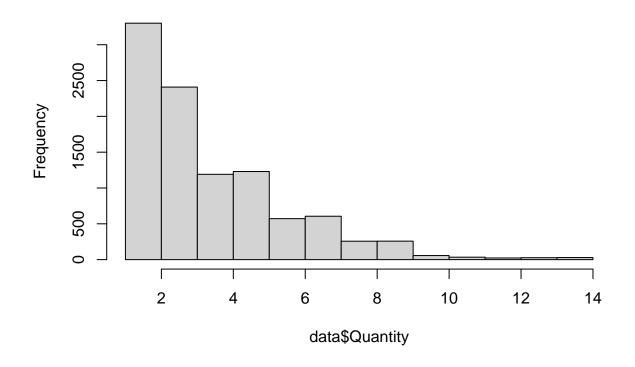
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 1.00 2.00 3.00 3.79 5.00 14.00

boxplot(data$Quantity)
```



#not many outliers - the #of products in each order is stable?
hist(data\$Quantity)

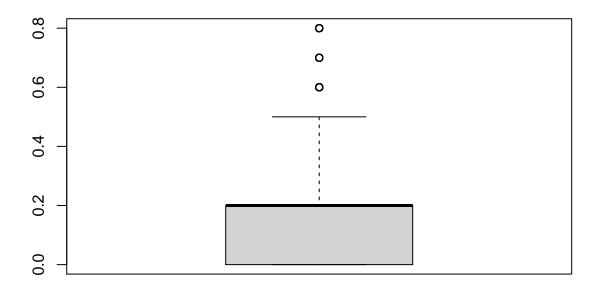
Histogram of data\$Quantity



```
#very skewed distribution - most of the orders have small #of items
summary(data$Discount)
```

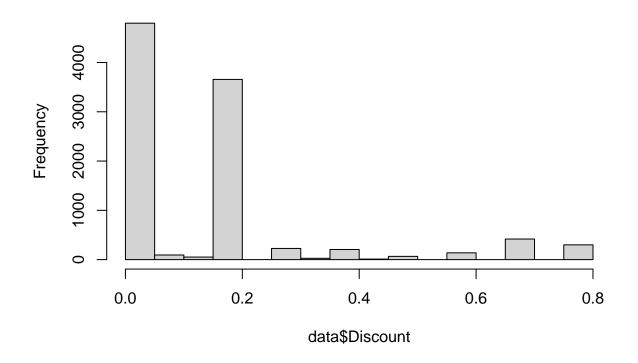
```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.0000 0.0000 0.2000 0.1562 0.2000 0.8000
```

boxplot(data\$Discount)



#a strange looking box dataplot? - median & 3rd quantile are the same (0.2) - not many orders have high hist(data\$Discount)

Histogram of data\$Discount



#most of the orders were placed without any discounts or with 20% off
summary(data\$Profit)

Min. 1st Qu. Median Mean 3rd Qu. Max.

29.364

8399.976

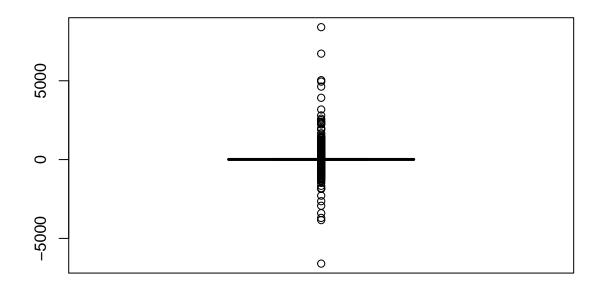
28.657

8.666

boxplot(data\$Profit)

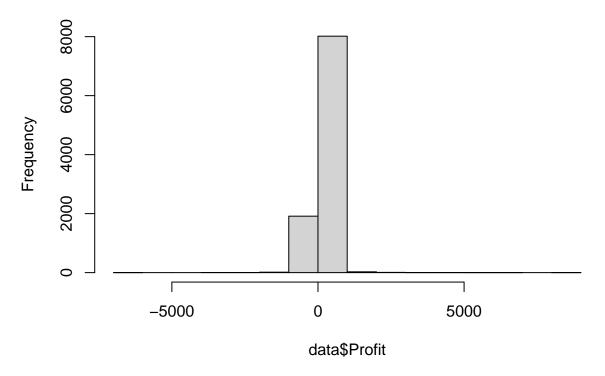
1.729

-6599.978



#most of the profits are outside of the box - but most of them clustered close to the box(not with so e hist(dataProfit)

Histogram of data\$Profit



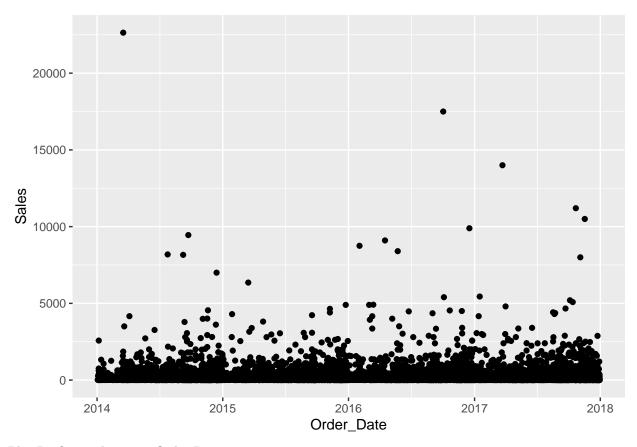
#most of the orders have profits ~1000 (or ~800?), and ~ -800

Remove the dot in the column names and replace with "__" to make variable names easier to handle:

```
##
    [1] "i__Row_ID"
                         "Order_ID"
                                          "Order_Date"
                                                            "Ship_Date"
       "Ship_Mode"
                                          "Customer_Name"
                                                           "Segment"
                         "Customer_ID"
    [9]
        "Country"
                         "City"
                                          "State"
                                                            "Postal_Code"
        "Region"
                         "Product_ID"
                                                            "Sub_Category"
   [13]
                                          "Category"
        "Product_Name"
                         "Sales"
                                          "Quantity"
                                                            "Discount"
   [17]
## [21] "Profit"
                         "diff_in_days"
```

Exploratory Data Analysis

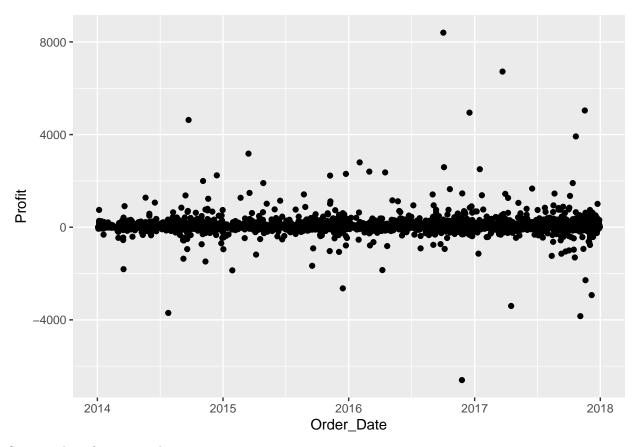
Plot Sales in relation to Order Date:



Plot Profit in relation to Order Date:

```
ggplot(data = data) +
geom_point(mapping = aes(x = Order_Date, y = Profit), xlab="Order Date", ylab="Profit")
```

Warning: Ignoring unknown parameters: xlab, ylab



Some outliers for certain days

```
table(data$'Sub_Category')
```

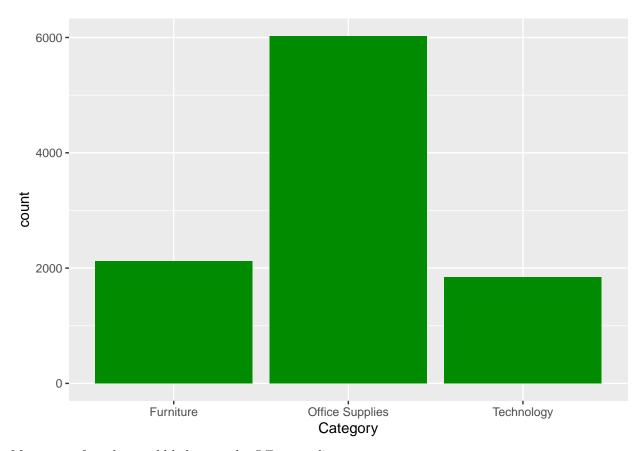
##						
##	Accessories	Appliances	Art	Binders	Bookcases	Chairs
##	775	466	796	1523	228	617
##	Copiers	Envelopes	Fasteners	Furnishings	Labels	Machines
##	68	254	217	957	364	115
##	Paper	Phones	Storage	Supplies	Tables	
##	1370	889	846	190	319	

look at the time range for these transactions, ie. start date for Order_Date column:

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## "2014-01-03" "2015-05-23" "2016-06-26" "2016-04-30" "2017-05-14" "2017-12-30"
#[1] min "2014-01-03", max "2017-12-30"
```

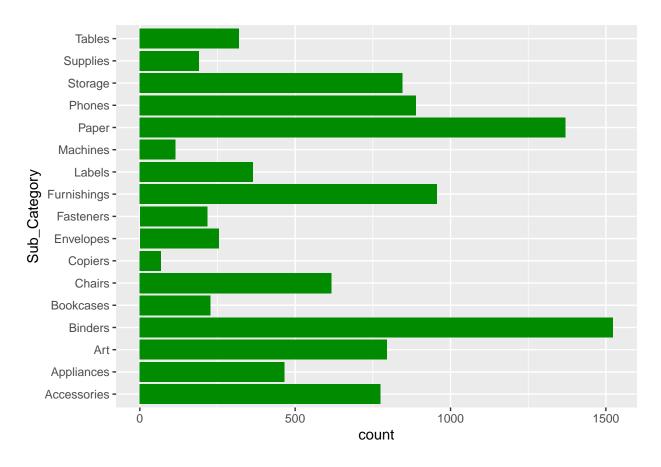
Basically this dataset covers transactions ranging from 2014-01-03 to 2017-12-30.

```
ggplot(data = data) +
geom_bar(mapping = aes(x = Category),fill="green4")
```



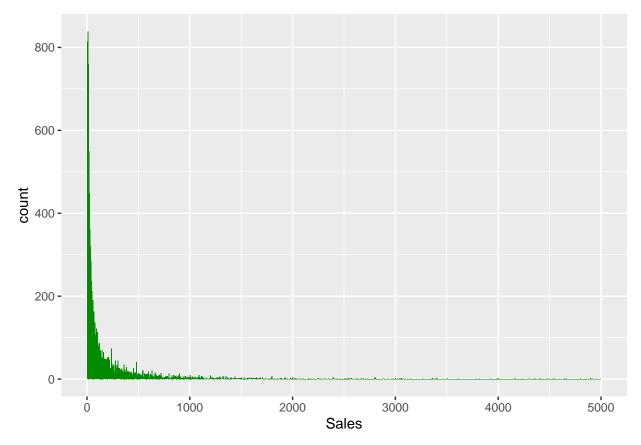
Most type of products sold belong to the Office supplies category.

```
ggplot(data = data) +
geom_bar(mapping = aes(y = 'Sub_Category'), fill="green4")
```



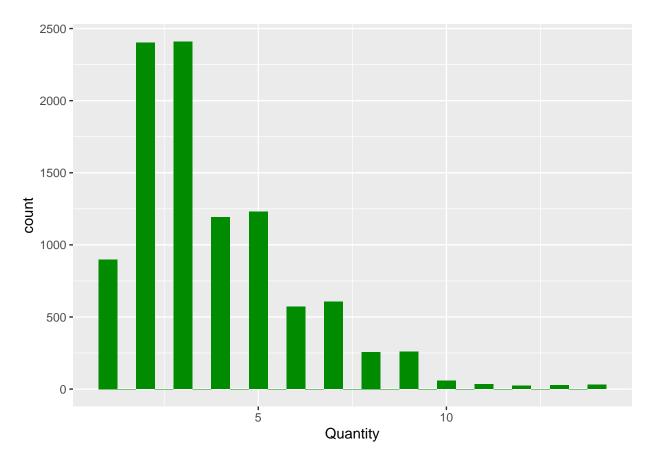
```
ggplot(data = data, mapping = aes(x = Sales)) +
    xlim(0, 5000) +
    geom_histogram(binwidth = 5,fill="green4")
```

- ## Warning: Removed 19 rows containing non-finite values (stat_bin).
- ## Warning: Removed 2 rows containing missing values (geom_bar).

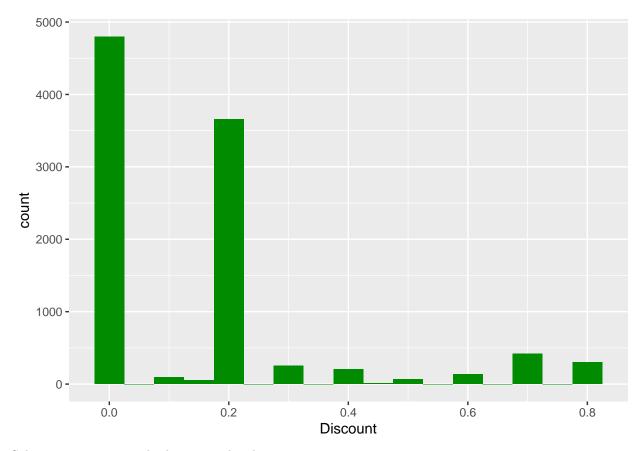


Most sales are very few items (<500).

```
ggplot(data = data, mapping = aes(x = Quantity)) +
geom_histogram(binwidth = 0.5,fill="green4")
```



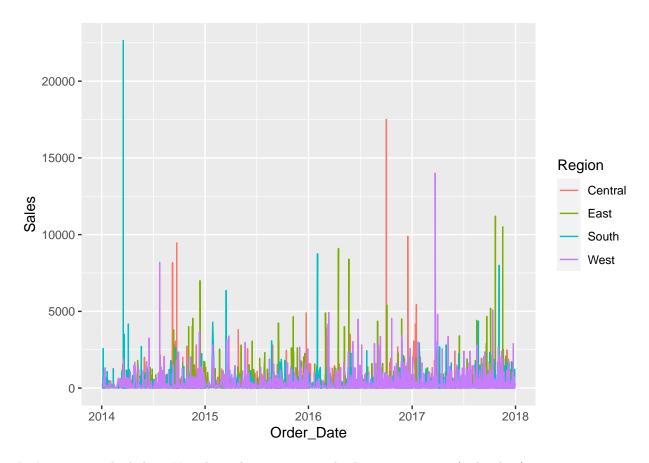
Warning: Ignoring unknown parameters: xlab



Sales transactions mostly do not involve discounts.

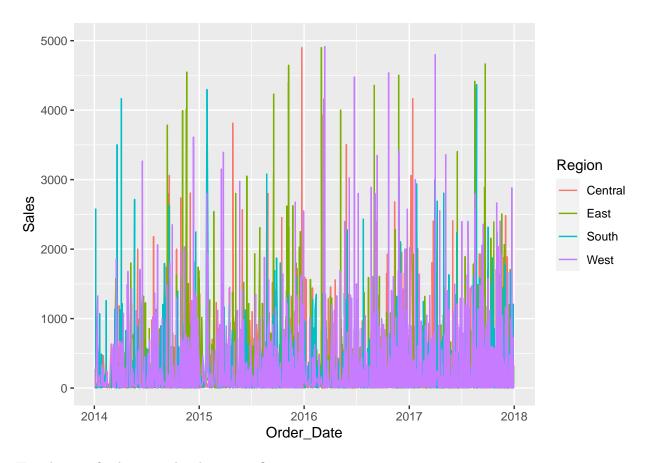
Visualise sales transactions by Region over time (order date).

```
ggplot(data, aes(Order_Date, Sales,color=Region)) +
    geom_line()
```



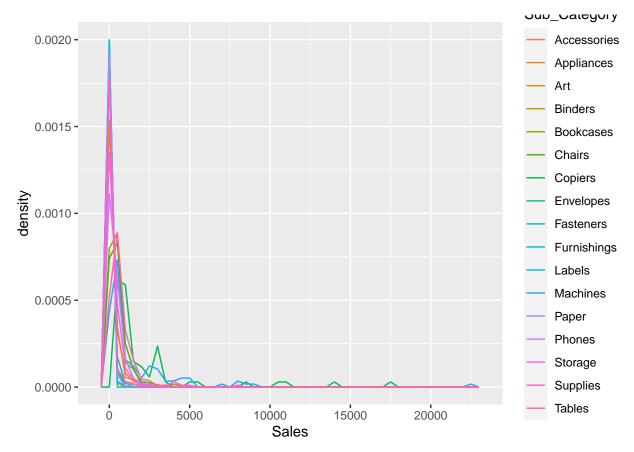
Let's zoom in a little bit - Visualise sales transactions by Region over time (order date).

```
ggplot(data, aes(Order_Date, Sales,color=Region)) +
   geom_line() +
   ylim(0,5000)
```



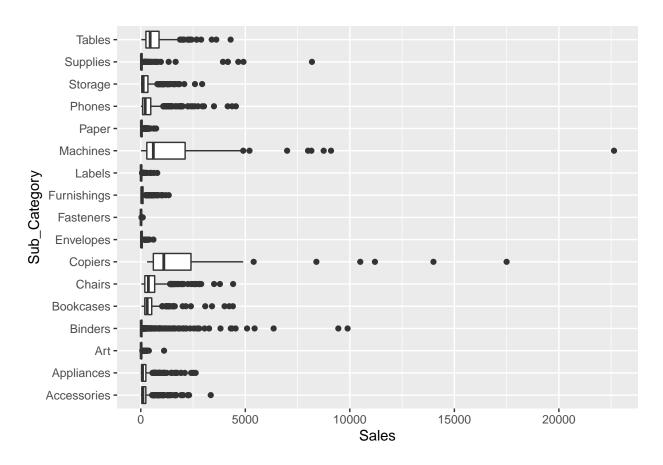
How does profit change with sub-category?

```
#density plot where the count is standardized, area under each frequency is 1
ggplot(data = data, mapping = aes(x = Sales, y = ..density..)) +
geom_freqpoly(mapping = aes(colour = Sub_Category), binwidth = 500)
```

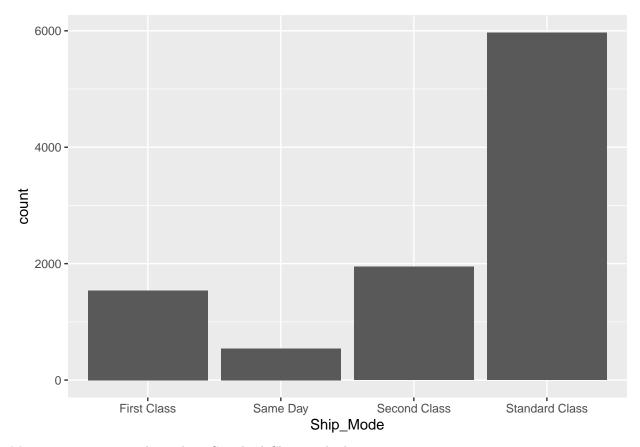


It looks like some categories of items ie. supplies or accessories have negative sales values. How does sales vary across sub category?

```
ggplot(data = data, mapping = aes(x = Sales, y = 'Sub_Category')) +
geom_boxplot()
```



```
ggplot(data =data, mapping = aes(x = Ship_Mode)) +
  geom_bar()
```

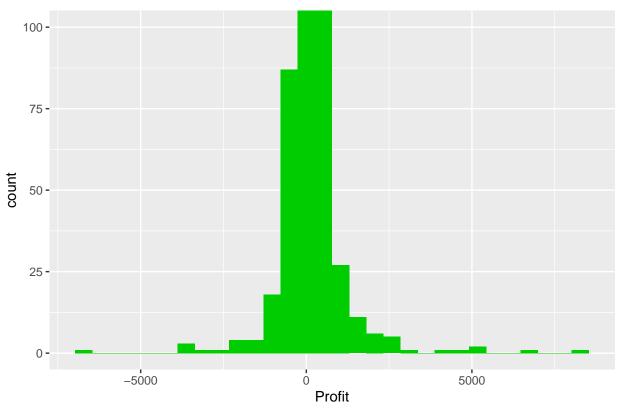


Most transactions are shipped via Standard Class method.

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

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

Profit Distribution



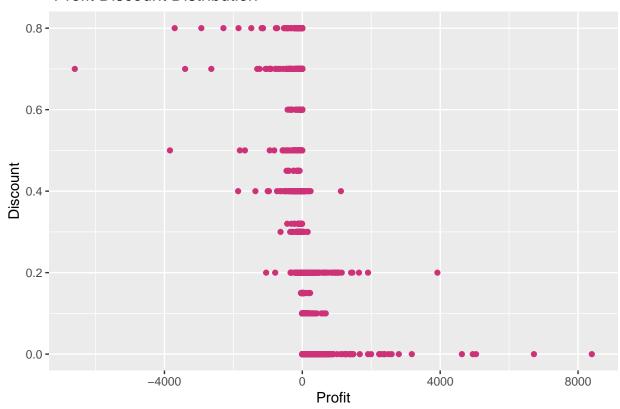
```
ggplot(data)+
geom_histogram(mapping=aes(x=Sales),fill="sienna3")+
coord_cartesian(ylim = c(0, 100))+labs(title=" Sales Distribution")
```

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

Sales Distribution 10075250005000 10000 Sales

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

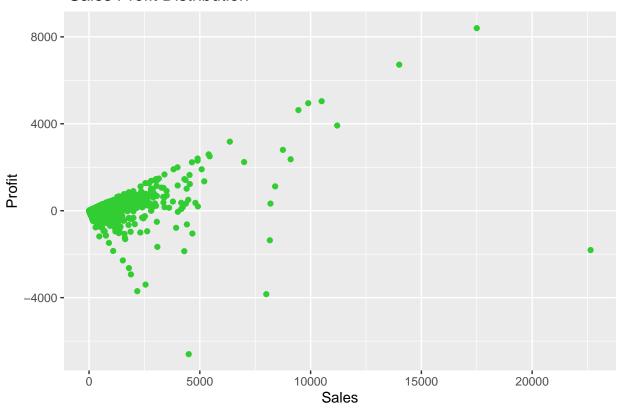
Profit Discount Distribution



Sales Profit

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

Sales Profit Distribution



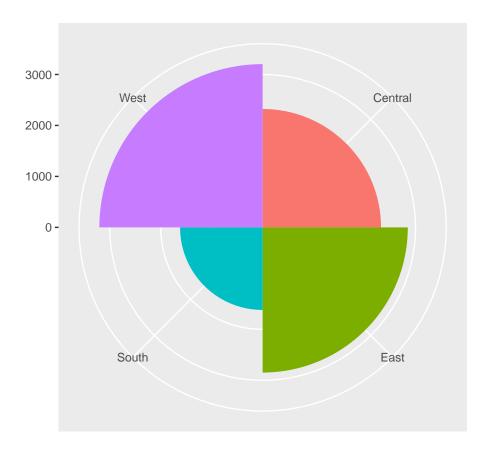
```
#product name and product id mismatch
data %>%
  distinct(Product_Name,Product_ID) %>%
  group_by(Product_ID) %>%
  filter(n()>1) %>%
  select(Product_ID)
```

```
## # 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(data$Category)</pre>
length(count_category)
## [1] 3
count_subcategory<-unique(data$Sub_Category)</pre>
length(count_subcategory)
## [1] 17
data %>%
 distinct(Category, Sub_Category)
##
             Category Sub_Category
## 1
            Furniture
                         Bookcases
## 2
            Furniture
                             Chairs
## 3 Office Supplies
                             Labels
## 4
            Furniture
                             Tables
## 5 Office Supplies
                            Storage
            Furniture Furnishings
## 6
## 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<-data %>%
                  select(Order_Date,Sales)
superstore_sales<-as_tibble(superstore_sales)</pre>
Transactions by region:
bar <- ggplot(data = data) +</pre>
  geom_bar(
    mapping = aes(x = Region, fill = Region),
    show.legend = FALSE,
    width = 1
 ) +
  theme(aspect.ratio = 1) +
 labs(x = NULL, y = NULL)
```

bar + coord_polar()

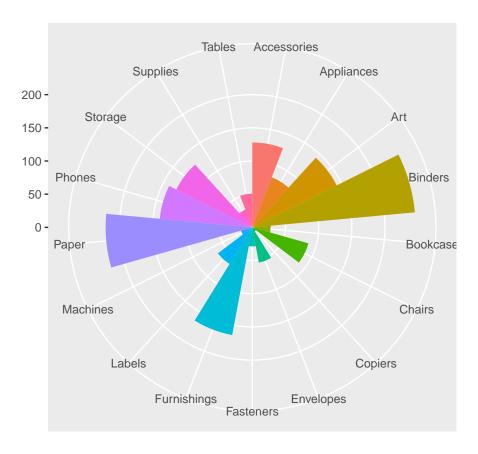


The above chart shows proportions of transactions from the different regions.

```
#Extracting the rows for South region, and sub-categories:
South <- data %>%
    select(Region, Sub_Category) %>%
    filter(Region == "South")

bar <- ggplot(data = South) +
    geom_bar(
        mapping = aes(x = Sub_Category, fill = Sub_Category),
        show.legend = FALSE,
        width = 1
    ) +
    theme(aspect.ratio = 1) +
    labs(x = NULL, y = NULL)

bar + coord_polar()</pre>
```

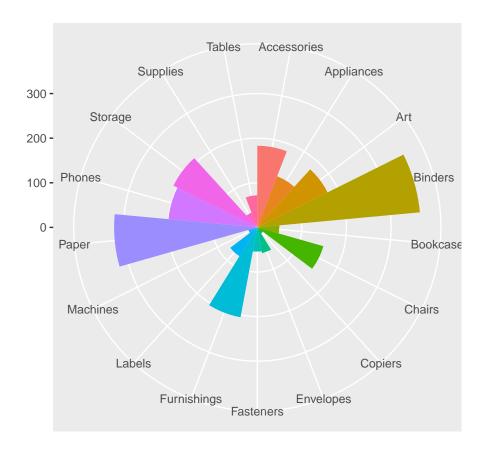


In the South, most transactions are Binders, Paper, or Furnishings.

```
#Extracting the rows for Central region, and sub-categories:
Central <- data %>%
    select(Region, Sub_Category) %>%
    filter(Region == "Central")

bar <- ggplot(data = Central) +
    geom_bar(
        mapping = aes(x = Sub_Category, fill = Sub_Category),
        show.legend = FALSE,
        width = 1
    ) +
    theme(aspect.ratio = 1) +
    labs(x = NULL, y = NULL)

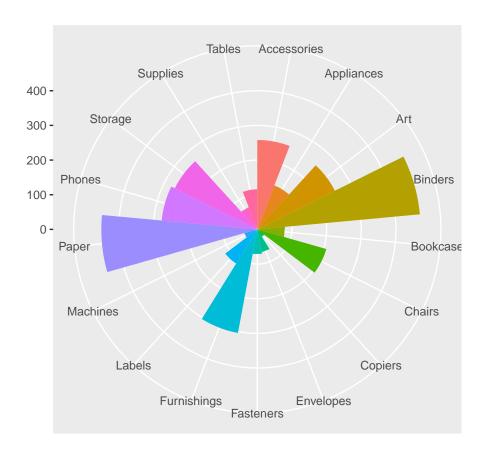
bar + coord_polar()</pre>
```



```
#Extracting the rows for West region, and sub-categories:
West <- data %>%
    select(Region, Sub_Category) %>%
    filter(Region == "West")

bar <- ggplot(data = West) +
    geom_bar(
        mapping = aes(x = Sub_Category, fill = Sub_Category),
        show.legend = FALSE,
        width = 1
    ) +
    theme(aspect.ratio = 1) +
    labs(x = NULL, y = NULL)

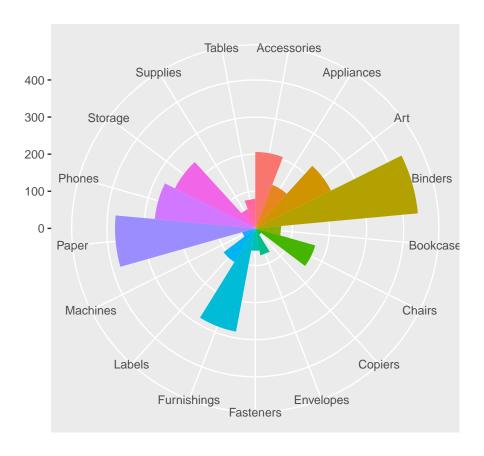
bar + coord_polar()</pre>
```



```
#Extracting the rows for East region, and sub-categories:
East <- data %>%
    select(Region, Sub_Category) %>%
    filter(Region == "East")

bar <- ggplot(data = East) +
    geom_bar(
        mapping = aes(x = Sub_Category, fill = Sub_Category),
        show.legend = FALSE,
        width = 1
    ) +
    theme(aspect.ratio = 1) +
    labs(x = NULL, y = NULL)

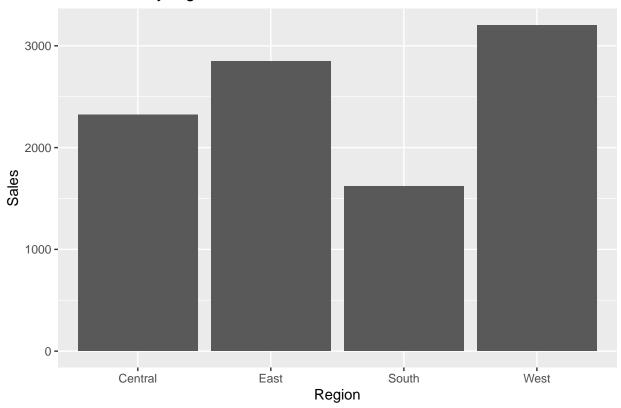
bar + coord_polar()</pre>
```



• bar charts of profits/sales by region

```
ggplot(data = data) +
  geom_bar(mapping = aes(x = Region, fill = Sales)) +
  ggtitle("Total Sales by region") +
  ylab("Sales")
```

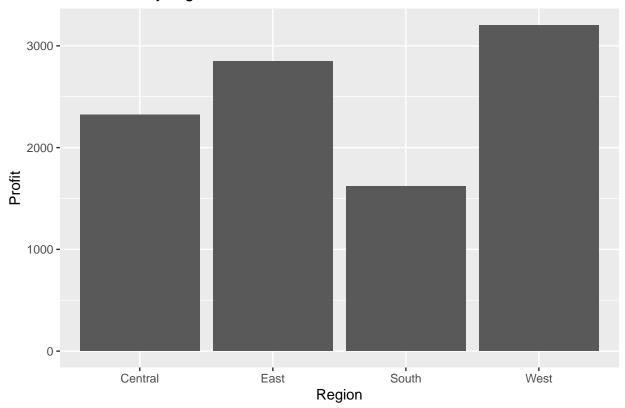
Total Sales by region



Total sales per region.

```
ggplot(data = data) +
  geom_bar(mapping = aes(x = Region, fill = Profit))+
  ggtitle("Total Profit by region")+
  ylab("Profit")
```

Total Profit by region



Look at relationship between numeric variables:

```
#subset the numeric variables:
numeric_vars<- c("Sales", "Quantity", "Discount", "Profit", "diff_in_days")
num_data <- data[numeric_vars]</pre>
```

We'll use a correlation matrix to look at the relationship between numeric variables:

```
cor(num_data)
```

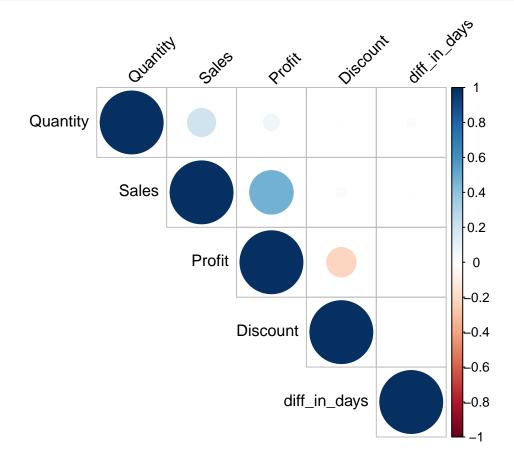
```
## Sales Quantity Discount Profit diff_in_days
## Sales 1.00000000 0.20079477 -0.0281901242 0.479064350 -0.0073535371
## Quantity 0.200794771 1.00000000 0.0086229703 0.066253189 0.0182984399
## Discount -0.028190124 0.00862297 1.0000000000 -0.219487456 0.0004084856
## Profit 0.479064350 0.06625319 -0.2194874564 1.000000000 -0.0046493531
## diff in days -0.007353537 0.01829844 0.0004084856 -0.004649353 1.000000000
```

```
#correlation matrix with statistical significance
cor_result=rcorr(as.matrix(num_data))

cor_result$r
```

```
## Sales Quantity Discount Profit diff_in_days
## Sales 1.000000000 0.20079477 -0.0281901242 0.479064350 -0.0073535371
## Quantity 0.200794771 1.00000000 0.0086229703 0.066253189 0.0182984399
```

```
corrplot(cor_result$r, type = "upper", order = "hclust", tl.col = "black", tl.srt = 45) #display only
```



Discount is negatively correlated with profit, whereas sales is positively correlated with profit. The time between order date and ship date (diff_in_days) is not correlated with sales, quantity, discount, or profit.

Data Preparation

```
#make a copy of the original dataset and copy to data1 data1 <- data
```

drop column Row ID because it is not necessary; it is the row number from the original excel file. The country variable is also not needed because all the values are United states. Customer_Name and Customer_ID give redundant information. So we will drop the Customer_Name column and keep only the Customer_ID column.

```
data1[,c("Row_ID","i__Row_ID", "Country", "Customer_Name")]<-NULL
head(data1)</pre>
```

```
Order ID Order Date Ship Date
                                                 Ship Mode Customer ID
                                                                         Segment
## 1 CA-2016-152156 2016-11-08 2016-11-11
                                             Second Class
                                                              CG-12520
                                                                        Consumer
                                             Second Class
                                                              CG-12520
## 2 CA-2016-152156 2016-11-08 2016-11-11
                                                                         Consumer
## 3 CA-2016-138688 2016-06-12 2016-06-16
                                             Second Class
                                                              DV-13045 Corporate
## 4 US-2015-108966 2015-10-11 2015-10-18 Standard Class
                                                              SO-20335
                                                                        Consumer
## 5 US-2015-108966 2015-10-11 2015-10-18 Standard Class
                                                              SO-20335
                                                                        Consumer
## 6 CA-2014-115812 2014-06-09 2014-06-14 Standard Class
                                                              BH-11710
                                                                        Consumer
##
                City
                           State Postal Code Region
                                                          Product ID
                                                                             Category
## 1
           Henderson
                        Kentucky
                                       42420
                                              South FUR-B0-10001798
                                                                            Furniture
## 2
           Henderson
                       Kentucky
                                       42420
                                              South FUR-CH-10000454
                                                                            Furniture
## 3
         Los Angeles California
                                       90036
                                               West OFF-LA-10000240 Office Supplies
## 4 Fort Lauderdale
                                              South FUR-TA-10000577
                        Florida
                                       33311
                                                                            Furniture
                                              South OFF-ST-10000760 Office Supplies
## 5 Fort Lauderdale
                        Florida
                                       33311
         Los Angeles California
## 6
                                       90032
                                               West FUR-FU-10001487
                                                                            Furniture
##
                                                                         Product_Name
     Sub_Category
## 1
        Bookcases
                                                   Bush Somerset Collection Bookcase
## 2
           Chairs
                        Hon Deluxe Fabric Upholstered Stacking Chairs, Rounded Back
## 3
           Labels
                          Self-Adhesive Address Labels for Typewriters by Universal
## 4
           Tables
                                      Bretford CR4500 Series Slim Rectangular Table
## 5
          Storage
                                                      Eldon Fold 'N Roll Cart System
##
  6
      Furnishings Eldon Expressions Wood and Plastic Desk Accessories, Cherry Wood
        Sales Quantity Discount
##
                                    Profit diff_in_days
## 1 261.9600
                     2
                            0.00
                                   41.9136
## 2 731.9400
                     3
                            0.00
                                                       3
                                  219.5820
                     2
                            0.00
                                                       4
## 3 14.6200
                                    6.8714
## 4 957.5775
                     5
                            0.45
                                -383.0310
                                                       7
      22.3680
                     2
                            0.20
                                    2.5164
                                                       7
## 5
                     7
                                                       5
## 6
      48.8600
                            0.00
                                   14.1694
```

For this K-means clustering we will use the numeric variabels only: which are sales, quantity, discount, profit, diff_in_days (columns 15 - 19). K means clustering is affected by the starting assignment points, so we will try with 25 different starting assignments (nstart = 25), and see which ones work the best.

(https://www.datanovia.com/en/blog/k-means-clustering-visualization-in-r-step-by-step-guide/)

```
#Compute K-means clustering with k=3 (3 initial distinct cluster centres)
set.seed(123)

results_kmeans <- kmeans(scale(data1[,(15:19)]), 3, nstart =25)

#kmeans clusters to show the group of the individuals
results_kmeans$cluster</pre>
```

```
##
  [38] \ 2\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 2\ 2\ 1\ 1\ 2\ 2\ 2\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 2\ 1\ 1\ 1\ 1\ 1\ 1\ 2\ 1
##
  [75] \ 1\ 3\ 3\ 1\ 3\ 1\ 1\ 1\ 1\ 2\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 3\ 2\ 1\ 2\ 2\ 1\ 3\ 1\ 2\ 1\ 3\ 2\ 1\ 1\ 2\ 1
##
##
 ##
 ##
 ##
 ##
 [334] \ 3\ 1\ 1\ 1\ 1\ 1\ 1\ 3\ 2\ 2\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 2\ 2\ 1\ 1\ 1\ 1\ 2\ 1\ 1\ 1\ 2\ 1\ 1\ 1\ 2\ 2
 ##
```

```
## [8733] 1 1 2 1 1 3 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 2 3 3 1 2 1 1 1 2 1 1 1 3 3 3 1
## [9584] 1 1 1 1 1 1 1 3 3 3 1 1 1 1 1 1 1 2 1 1 3 1 1 1 2 1 1 2 1 1 2 2 1 3 1 1
## [9769] 2 1 1 1 1 1 3 3 3 2 3 3 1 1 1 1 1 1 2 1 1 1 2 1 1 3 3 1 3 3 1 3 2 1 1 1
## [9991] 1 1 1 1
```

summary(results_kmeans)

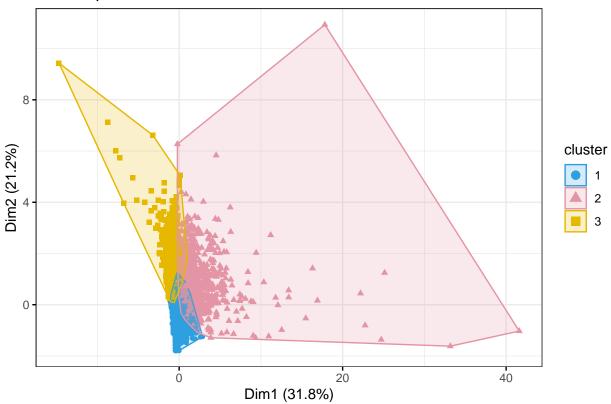
```
##
                Length Class Mode
## cluster
                9994
                       -none- numeric
## centers
                  15
                       -none- numeric
## totss
                   1
                       -none- numeric
## withinss
                   3
                       -none- numeric
## tot.withinss
                   1
                       -none- numeric
                   1
                       -none- numeric
## betweenss
```

```
## size 3 -none- numeric
## iter 1 -none- numeric
## ifault 1 -none- numeric
```

Plot K-means

The factoextra package contains a function called fviz_cluster() which can be used to visualize kmeans clusters. The input required is the original dataset, and the kmeans results. These are used to produce plots which show points that represent observations.

Cluster plot



 ${\it Reduce\ dimensions\ using\ Principal\ Component\ Analysis}.$

```
results_pca <- prcomp(data1[,(15:19)], scale=TRUE)
#Coordinates of individual observations
indiv_coordinates <- as.data.frame(get_pca_ind(results_pca)$coord)</pre>
```

```
#Add clusters obtained through the Kmeans algorithm
indiv_coordinates$cluster <- factor(results_kmeans$cluster)

#Add region from the dataset
indiv_coordinates$Region <- data1$Region

#look at the first few rows of individual coordinates
head(indiv_coordinates)

### Dim 1 Dim 2 Dim 3 Dim 4 Dim 5 cluster Region
```

```
##
                     Dim.2
                                Dim.3
                                             Dim.4
                                                         Dim.5 cluster Region
## 1 0.04520418 -1.13666870 0.3612739 0.0807637427 0.30768311
                                                                    1 South
## 2 1.15718390 -0.84275631 0.4252513 0.1851981706 0.21856052
                                                                    1 South
## 3 -0.31072375 -1.08484635 -0.2274155 -0.0007838382 0.15040037
                                                                        West
                                                                    1
## 4 -0.63620673 2.24187253 -1.2663321 0.5805617103 1.55922466
                                                                    3 South
## 5 -0.58444157 -0.08714015 -1.6947210 0.7880697439 -0.05040709
                                                                   1 South
## 6 0.39080002 0.44622564 -0.7312599 -1.4739348647 -0.19665673
                                                                    2 West
```

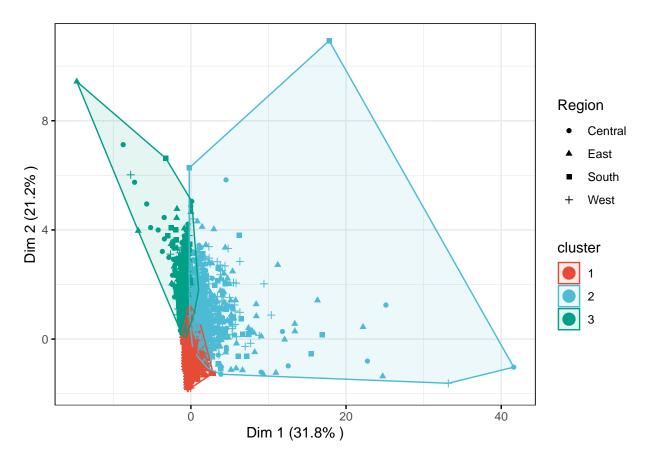
Percentage of variance explained by dimensions.

```
eigenvalue <- round(get_eigenvalue(results_pca), 1)
variance.percent <- eigenvalue$variance.percent
head(eigenvalue)</pre>
```

```
eigenvalue variance.percent cumulative.variance.percent
## Dim.1
              1.6
                               31.8
## Dim.2
                               21.2
                                                            53.0
               1.1
## Dim.3
               1.0
                               20.0
                                                            73.0
## Dim.4
                               17.6
                                                            90.6
               0.9
## Dim.5
               0.5
                                9.4
                                                           100.0
```

```
#To visualize the k-means clusters:

ggscatter(
  indiv_coordinates, x = "Dim.1", y = "Dim.2",
  color = "cluster", palette = "npg", ellipse = TRUE, ellipse.type = "convex", #adding the concentra
  shape = "Region", size = 1.5, legend = "right", ggtheme = theme_bw(),
    xlab = paste0("Dim 1 (", variance.percent[1], "% )" ),
    ylab = paste0("Dim 2 (", variance.percent[2], "% )" )
) +
    stat_mean(aes(color = cluster), size = 4) #stat_mean is used for adding the cluster centroid
```



The clustering plot shows that the groups are very close together, and overlap slightly. The clusters could be further apart with some tuning.

Model

Evaluation

Deployment

Responsible ML Framework

Conclusion

References

https://www.datanovia.com/en/blog/k-means-clustering-visualization-in-r-step-by-step-guide/https://www.tidymodels.org/learn/statistics/k-means/