STA 380 Exam-II

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Link to GitHub Repository

This markdown has been prepared as a submission for STA 380: Introduction to Machine Learning by **Parthiv Borgohain (MSBA, pb25347), Ruchi Sharma (MSBA, rs58898), Saurabh Arora (MSBA,sa55445) and Soumith Reddy Palreddy (MSBA, sp52466)**

Probability Practice

Question:

Part A. Visitors to your website are asked to answer a single survey question before they get access to the content on the page. Among all of the users, there are two categories: Random Clicker (RC), and Truthful Clicker (TC). There are two possible answers to the survey: yes and no. Random clickers would click either one with equal probability. You are also giving the information that the expected fraction of random clickers is 0.3. After a trial period, you get the following survey results: 65% said Yes and 35% said No. What fraction of people who are truthful clickers answered yes? Hint: use the rule of total probability.

Part B. Imagine a medical test for a disease with the following two attributes:

```
The sensitivity is about 0.993. That is, if someone has the disease, there is a probability of 0.993 tha

The specificity is about 0.9999. This means that if someone doesn't have the disease, there is probabili

In the general population, incidence of the disease is reasonably rare: about 0.0025% of all people have
```

Suppose someone tests positive. What is the probability that they have the disease?

Part A.

P(Y|RC) = P(N|RC) = 0.5
P(RC) = 0.3
P(Y) = 0.65 => P(N) = 0.35
=> 0.65 = 0.7 X P(Y|TC) + 0.3 X 0.5
=> P(Y|TC) = 0.714

Part B.

P(P|H) = 0.993
P($_{P|}$H) = 0.9999
P(H) = 0.000025

=> P(H|P) = 0.000025 X 0.993 / [(0.000025 x 0.993) + (1 - 0.9999) x (1 - 0.000025)]
=> P(H|P) = 0.198882413

Wrangling the Billboard Top 100

Part A

```
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 dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(dplyr)
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
billboard=read.csv('billboard.csv')
summary(billboard)
```

```
##        X              url              week_id          week_position
##  Min.   :     1   Length:327895      Length:327895      Min.   :  1.0
##  1st Qu.: 81975   Class :character   Class :character   1st Qu.: 25.5
##  Median :163948   Mode  :character   Mode  :character   Median : 50.0
##  Mean   :163948                                         Mean   : 50.5
##  3rd Qu.:245922                                         3rd Qu.: 75.0
##  Max.   :327895                                         Max.   :100.0
##
##      song            performer           song_id             instance
##  Length:327895      Length:327895      Length:327895      Min.   : 1.000
##  Class :character   Class :character   Class :character   1st Qu.: 1.000
```

```
##  Mode  :character   Mode  :character   Mode  :character   Median : 1.000
##                                                          Mean   : 1.073
##                                                          3rd Qu.: 1.000
##                                                          Max.   :10.000
##
##  previous_week_position peak_position    weeks_on_chart       year
##  Min.   :  1.0          Min.   :  1.00   Min.   : 1.000   Min.   :1958
##  1st Qu.: 23.0          1st Qu.: 14.00   1st Qu.: 4.000   1st Qu.:1974
##  Median : 47.0          Median : 39.00   Median : 7.000   Median :1989
##  Mean   : 47.6          Mean   : 41.36   Mean   : 9.154   Mean   :1989
##  3rd Qu.: 72.0          3rd Qu.: 66.00   3rd Qu.:13.000   3rd Qu.:2005
##  Max.   :100.0          Max.   :100.00   Max.   :87.000   Max.   :2021
##  NA's   :31954
##       week
##  Min.   : 1.00
##  1st Qu.:14.00
##  Median :27.00
##  Mean   :26.59
##  3rd Qu.:40.00
##  Max.   :53.00
##
```

```
df = billboard

head(sort(df$weeks_on_chart, decreasing = TRUE), n = 10)
```

```
##  [1] 87 86 85 84 83 82 81 80 79 79
```

```
df2 <- df %>%
  group_by(performer, song) %>%
  summarize(countt = sum(weeks_on_chart))
```

```
## `summarise()` has grouped output by 'performer'. You can override using the
## `.groups` argument.
```

```
df2
```

```
## # A tibble: 29,389 x 3
## # Groups:   performer [10,061]
##    performer                song                                          countt
##    <chr>                    <chr>                                          <int>
##  1 'N Sync                  (God Must Have Spent) A Little More Time On ~    253
##  2 'N Sync                  Bye Bye Bye                                      276
##  3 'N Sync                  Gone                                             300
##  4 'N Sync                  I Drive Myself Crazy                              78
##  5 'N Sync                  I Want You Back                                  300
##  6 'N Sync                  It's Gonna Be Me                                 325
##  7 'N Sync                  Pop                                              120
##  8 'N Sync                  Tearin' Up My Heart                               1
##  9 'N Sync                  This I Promise You                               351
## 10 'N Sync & Gloria Estefan Music Of My Heart                               210
## # ... with 29,379 more rows
## # i Use `print(n = ...)` to see more rows
```

```
head(sort(df2$countt, decreasing = TRUE), n = 10)
```

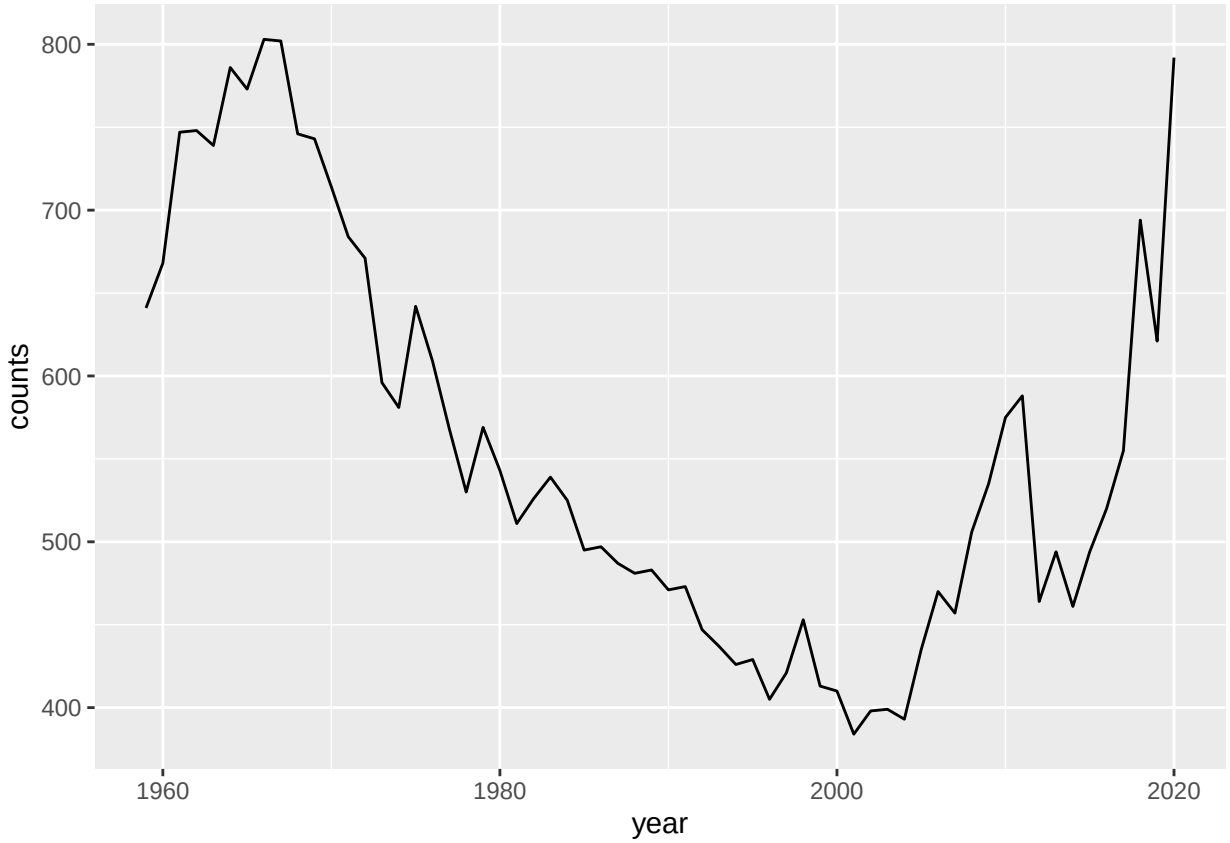
```
##  [1] 3828 3160 2926 2926 2415 2346 2346 2145 2145 2080
```

```
df2 <- df2[order(-df2$countt),]

df3 <- df %>%
  group_by(song_id) %>%
  summarize(countt = sum(weeks_on_chart)) %>%
  head

summary(df3)
```

```
##    song_id              countt
##  Length:6           Min.   :  3.0
##  Class :character   1st Qu.: 15.0
##  Mode  :character   Median : 30.0
##                     Mean   : 94.0
##                     3rd Qu.:168.8
##                     Max.   :276.0
```

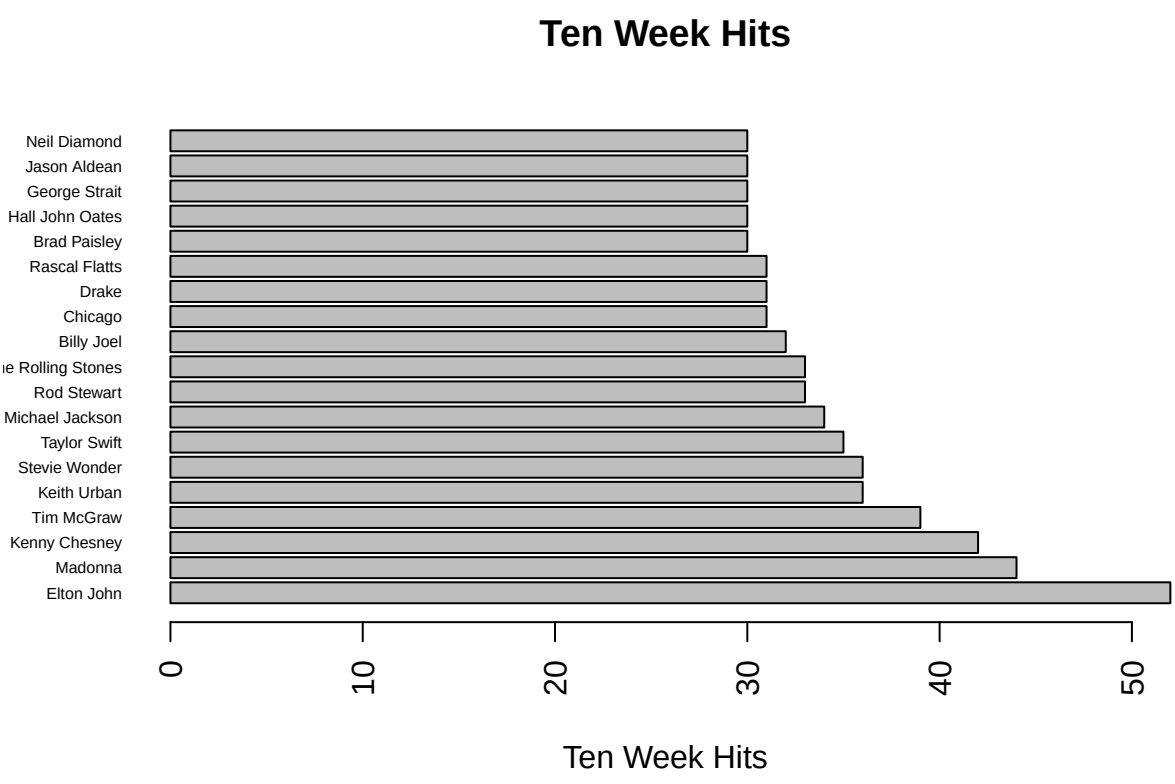
Part B.

```
df4 <- df %>%
  group_by(year) %>%
  summarize(counts = length(unique(song)))

df4 = df4[-1,]
df4 = df4[-63,]

ggplot(df4) +
  geom_line(aes(x=year, y=counts))
```



Part C.

```
df5 <- df[which(df$weeks_on_chart >= 10),]

df6 <- df5 %>%
  group_by(performer) %>%
  summarize(counts = length(unique(song)))

df6 <- df6[which(df6$counts >= 30),]
df6 <- df6[order(-df6$counts),]

barplot(df6$counts, main="Ten Week Hits",
        xlab="Ten Week Hits", names.arg = df6$performer,
        horiz = TRUE, las=2, cex.names=.5)
```



Visual Story Telling Part 1: Green Buildings

```
library(readr)
library(plyr)
```

```
## ------------------------------------------------------------------------------
```

```
## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)
```

```
## ------------------------------------------------------------------------------
```

```
##
## Attaching package: 'plyr'
```

```
## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

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

```
library(reshape2)
```

```
##
## Attaching package: 'reshape2'
```

```
## The following object is masked from 'package:tidyr':
##
##     smiths
```

```
greenbuildings <- read_csv("greenbuildings.csv")
```

```
## Rows: 7894 Columns: 23
```

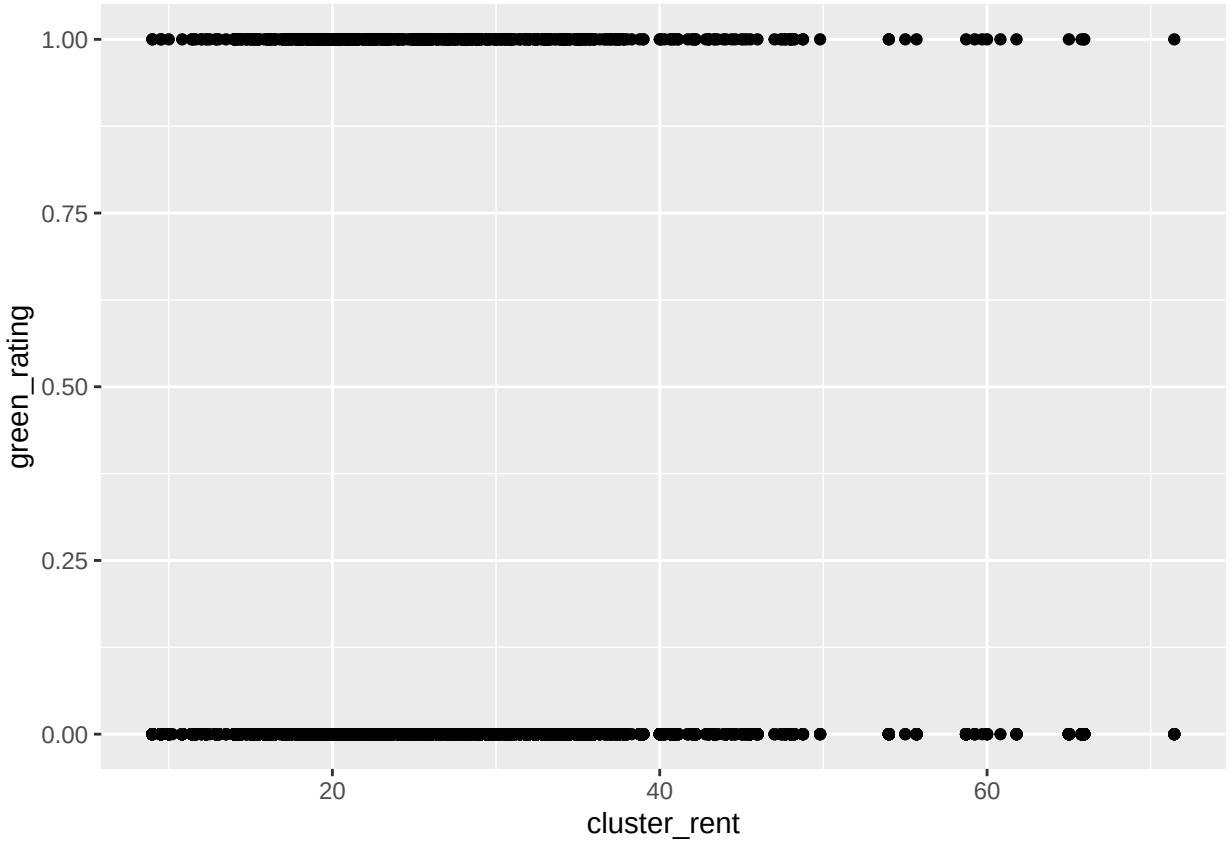
```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (23): CS_PropertyID, cluster, size, empl_gr, Rent, leasing_rate, stories...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
df = greenbuildings
summary(df)
```

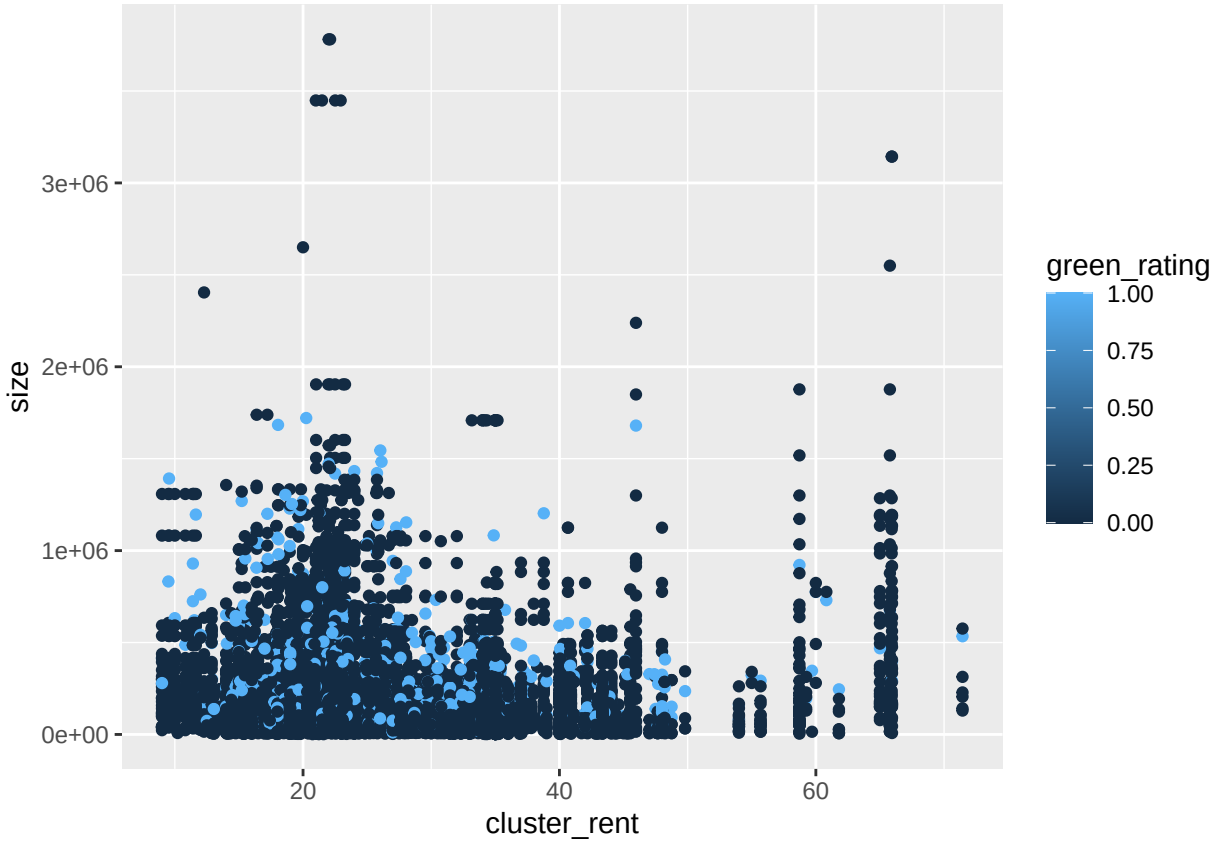
```
##  CS_PropertyID        cluster            size            empl_gr
##  Min.   :      1   Min.   :   1.0   Min.   :   1624   Min.   :-24.950
##  1st Qu.: 157452   1st Qu.: 272.0   1st Qu.:  50891   1st Qu.:  1.740
##  Median : 313253   Median : 476.0   Median : 128838   Median :  1.970
##  Mean   : 453003   Mean   : 588.6   Mean   : 234638   Mean   :  3.207
##  3rd Qu.: 441188   3rd Qu.:1044.0   3rd Qu.: 294212   3rd Qu.:  2.380
##  Max.   :6208103   Max.   :1230.0   Max.   :3781045   Max.   : 67.780
##                                                       NA's   :74
##       Rent         leasing_rate       stories            age
##  Min.   :  2.98   Min.   :  0.00   Min.   :  1.00   Min.   :  0.00
##  1st Qu.: 19.50   1st Qu.: 77.85   1st Qu.:  4.00   1st Qu.: 23.00
##  Median : 25.16   Median : 89.53   Median : 10.00   Median : 34.00
##  Mean   : 28.42   Mean   : 82.61   Mean   : 13.58   Mean   : 47.24
##  3rd Qu.: 34.18   3rd Qu.: 96.44   3rd Qu.: 19.00   3rd Qu.: 79.00
##  Max.   :250.00   Max.   :100.00   Max.   :110.00   Max.   :187.00
##
##    renovated         class_a          class_b           LEED
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.000000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000000
##  Median :0.0000   Median :0.0000   Median :0.0000   Median :0.000000
##  Mean   :0.3795   Mean   :0.3999   Mean   :0.4595   Mean   :0.006841
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.000000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.000000
##
```

```
##    Energystar       green_rating          net            amenities
##  Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :0.0000
##  1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.0000
##  Median :0.00000   Median :0.00000   Median :0.00000   Median :1.0000
##  Mean   :0.08082   Mean   :0.08677   Mean   :0.03471   Mean   :0.5266
##  3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:1.0000
##  Max.   :1.00000   Max.   :1.00000   Max.   :1.00000   Max.   :1.0000
##
##   cd_total_07     hd_total07    total_dd_07   Precipitation
##  Min.   :  39   Min.   :   0   Min.   :2103   Min.   :10.46
##  1st Qu.: 684   1st Qu.:1419   1st Qu.:2869   1st Qu.:22.71
##  Median : 966   Median :2739   Median :4979   Median :23.16
##  Mean   :1229   Mean   :3432   Mean   :4661   Mean   :31.08
##  3rd Qu.:1620   3rd Qu.:4796   3rd Qu.:6413   3rd Qu.:43.89
##  Max.   :5240   Max.   :7200   Max.   :8244   Max.   :58.02
##
##    Gas_Costs        Electricity_Costs  cluster_rent
##  Min.   :0.009487   Min.   :0.01780   Min.   : 9.00
##  1st Qu.:0.010296   1st Qu.:0.02330   1st Qu.:20.00
##  Median :0.010296   Median :0.03274   Median :25.14
##  Mean   :0.011336   Mean   :0.03096   Mean   :27.50
##  3rd Qu.:0.011816   3rd Qu.:0.03781   3rd Qu.:34.00
##  Max.   :0.028914   Max.   :0.06280   Max.   :71.44
##
```

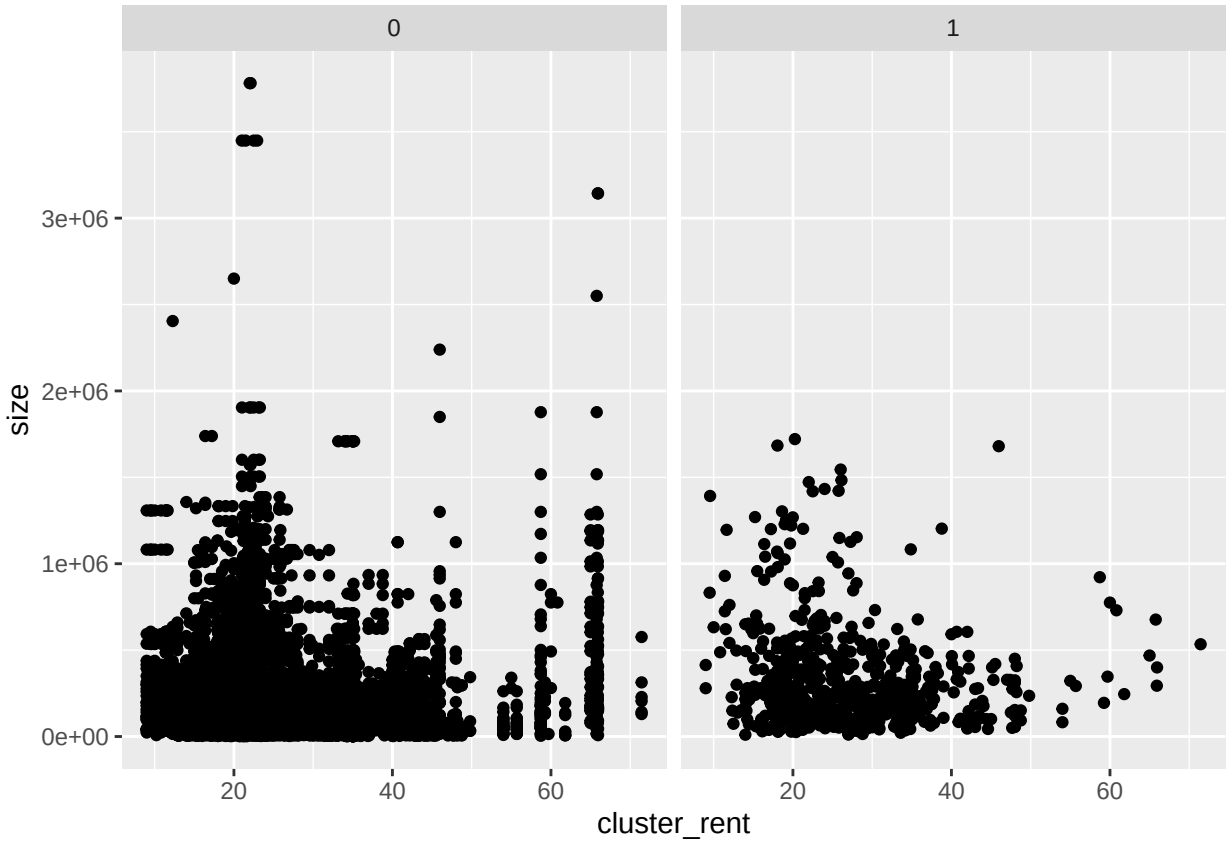
```
# Looking at distributions across some pair combinations

library(tidyverse)

ggplot(df) +
  geom_point(aes(x=cluster_rent, y=green_rating)) # almost similar distribution
```



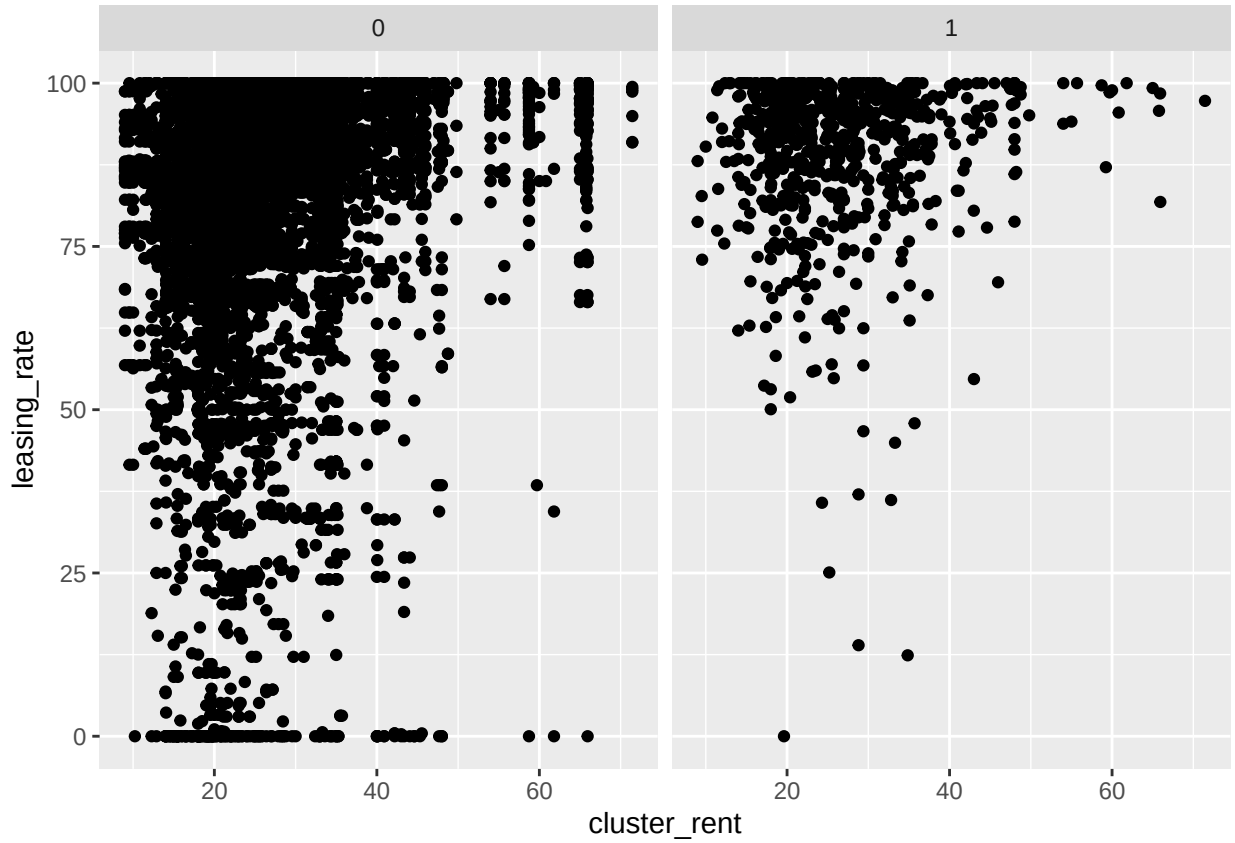

```
ggplot(df) +
  geom_point(aes(x=cluster_rent, y=size, color=green_rating))
```




```
ggplot(df) +
  geom_point(aes(x=cluster_rent, y=size)) +
  facet_wrap(~green_rating)
```

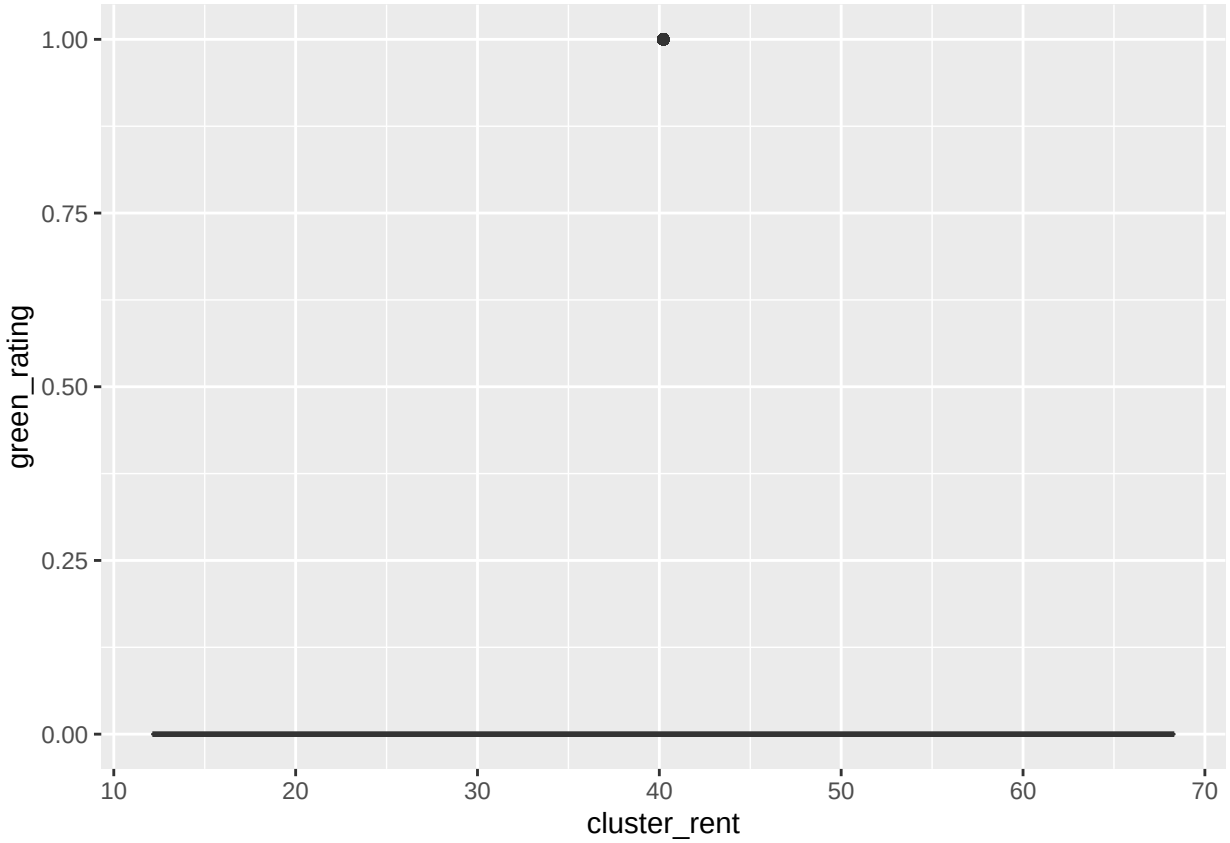



```
ggplot(df) +
  geom_point(aes(x=cluster_rent, y=leasing_rate)) +
  facet_wrap(~green_rating)
```



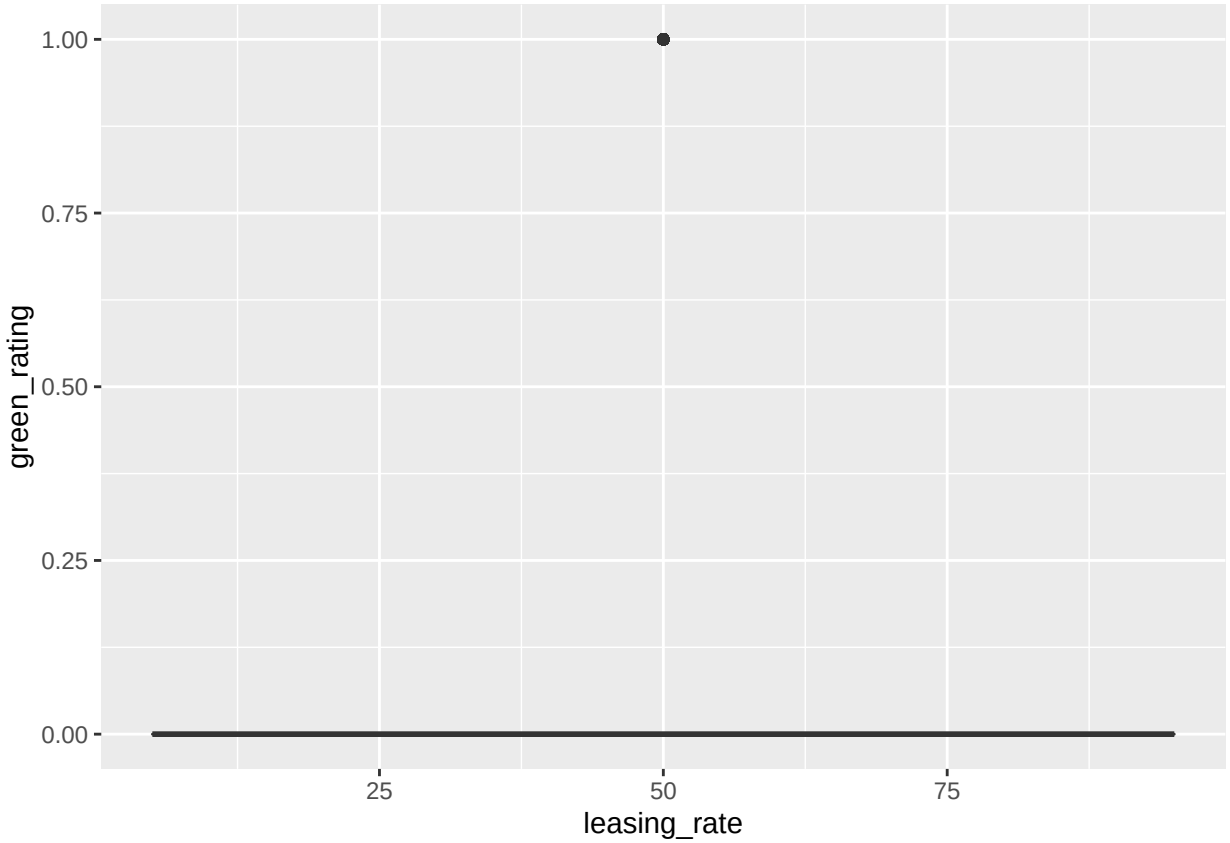

```
ggplot(df) +
  geom_boxplot(aes(x=cluster_rent, y=green_rating))
```

```
## Warning: Continuous x aesthetic -- did you forget aes(group=...)?
```




```
ggplot(df) +
  geom_boxplot(aes(x=leasing_rate, y=green_rating))
```

```
## Warning: Continuous x aesthetic -- did you forget aes(group=...)?
```




```
# Splitting the data frame into green vs non-green

green = subset(df ,df$green_rating == 1)
non_green = subset(df ,df$green_rating!= 1)

median(green$Rent)
```

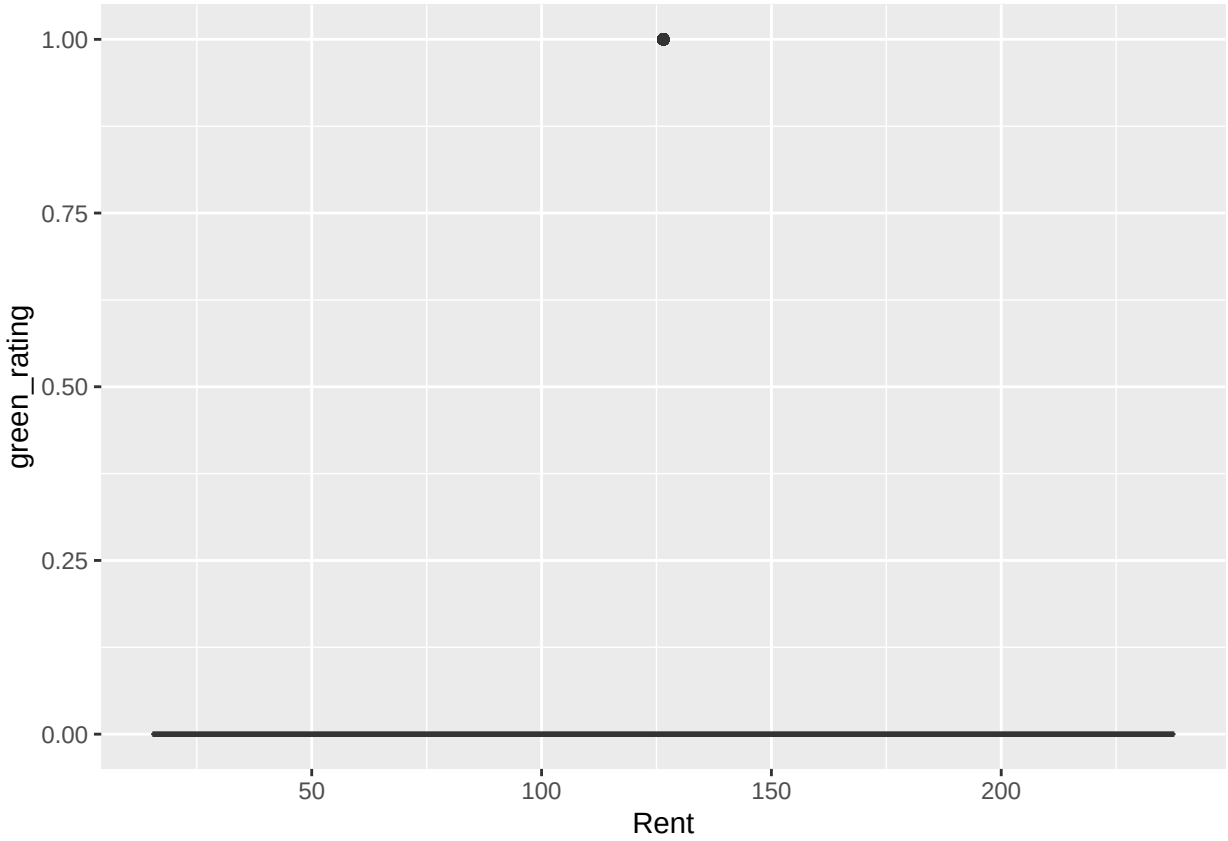
```
## [1] 27.6
```

```
median(non_green$Rent)
```

```
## [1] 25
```

```
ggplot(df) +
  geom_boxplot(aes(x=Rent, y=green_rating))
```

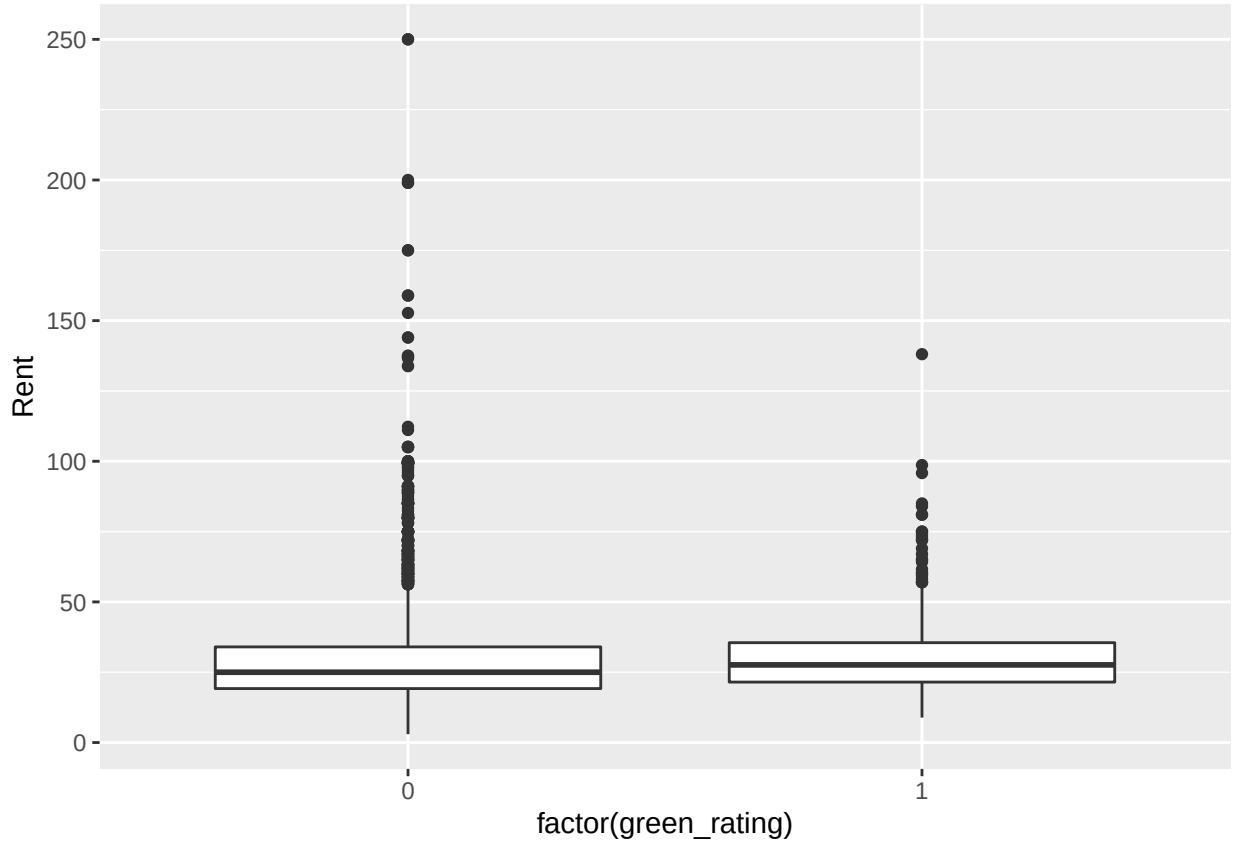
```
## Warning: Continuous x aesthetic -- did you forget aes(group=...)?
```




```
# Median Rent for Green Buildings > Median Rent for Non Green Buildings

# Looking at the statistics for average rent

df %>%
  summarize(avg_rent = mean(Rent),
            sd_rent = sd(Rent),
            q05_rent = quantile(Rent, 0.05),
            q95_rent = quantile(Rent, 0.95)) %>%
  round(1)
```

```
##   avg_rent sd_rent q05_rent q95_rent
## 1     28.4    15.1     12.5     51.8
```

```
ggplot(df) +
  geom_boxplot(aes(x=factor(green_rating), y=Rent))
```



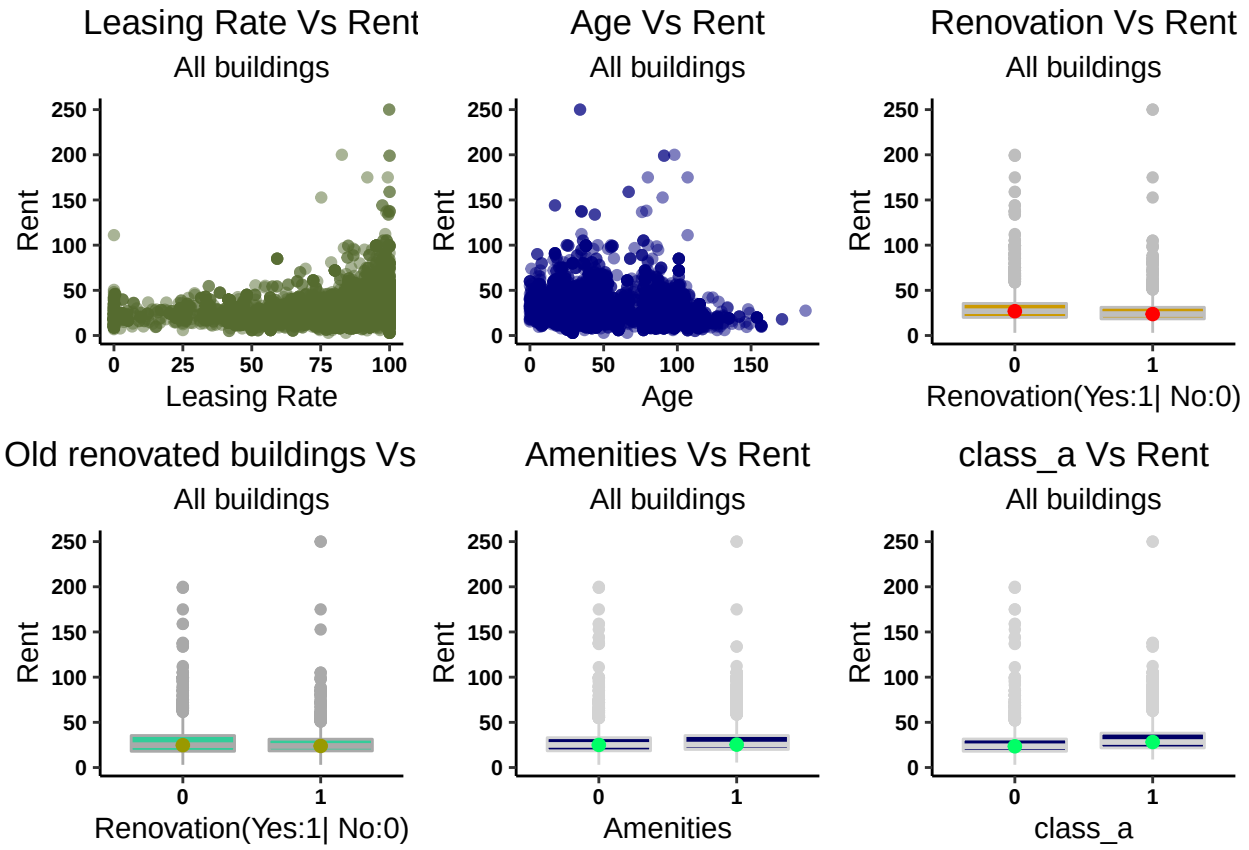

```
df %>%
  group_by(green_rating) %>%
  summarize(avg_rent = mean(Rent),
            sd_rent = sd(Rent),
            q05_rent = quantile(Rent, 0.05),
            q95_rent = quantile(Rent, 0.95)) %>%
  round(1)
```

```
##   avg_rent sd_rent q05_rent q95_rent
## 1     28.4    15.1     12.5     51.8
```

```
# Plotting a set of graphs to see what other factors impact the Rent

knitr::opts_chunk$set(fig.width = 20, fig.height = 10)

# Leasing_rate

leasing_rate = ggplot(df, aes(x=leasing_rate, y=Rent))+
  theme_classic()+geom_point(colour = "darkolivegreen", size = 1.5, alpha = 0.5)+
  labs(x = "Leasing Rate", y = "Rent",title = "Leasing Rate Vs Rent",
               subtitle = "All buildings") +
  theme(axis.text.x =
          element_text(face = "bold", color = "black", size = 8, angle = 0),
        axis.text.y = element_text(face="bold", color="black",
        size=8, angle=0),plot.title = element_text(hjust = 0.5),
```

```
        plot.subtitle = element_text(hjust = 0.5))

# Age

age = ggplot(df, aes(x = age,y = Rent)) + theme_classic() +
        geom_point(colour = "navyblue", size = 1.5,alpha = 0.5)+
        labs(x = "Age", y = "Rent",title = "Age Vs Rent",
        subtitle = "All buildings") + theme(axis.text.x = element_text
        (face="bold",color="black", size=8, angle=0),
        axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
        plot.title = element_text(hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5))

# Renovations

df$renovated = as.factor(df$renovated)
renovation <- ggplot(df, aes(x = renovated, y = Rent)) +
  geom_boxplot(colour = "grey", fill = "#CC9900") + theme_classic() +
  labs(x = "Renovation(Yes:1| No:0)", y = "Rent",title = "Renovation Vs Rent",
       subtitle = "All buildings") + theme(axis.text.x = element_text(
       face="bold",color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5)) + stat_summary(fun=median,
       geom="point", shape=20, size=3, color="red", fill="red")

# Renovations in buildings older than 30 years

renovation_30_years_more = subset(df, df$age >=30)
renovation_30 <- ggplot(renovation_30_years_more,
       aes(x = renovated, y = Rent)) + geom_boxplot(colour = "darkgrey",
       fill = "#33CC99") + theme_classic() + labs(x = "Renovation(Yes:1| No:0)",
       y = "Rent",title = "Old renovated buildings Vs Rent",
       subtitle = "All buildings") + theme(axis.text.x = element_text(
       face="bold",color="black", size=8, angle=0), axis.text.y = element_text(
       face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5)) + stat_summary(fun=median,
       geom="point", shape=20, size=3, color="#999900", fill="red")

# Amenities

df$amenities = as.factor(df$amenities)
amenities <- ggplot(df, aes(x = amenities, y = Rent)) +
  geom_boxplot(colour = "lightgrey", fill = "#000066") + theme_classic() +
  labs(x = "Amenities", y = "Rent",title = "Amenities Vs Rent",
       subtitle = "All buildings") + theme(axis.text.x = element_text(
       face="bold",color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold", color="black", size=8,angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5))+
       stat_summary(fun=median, geom="point", shape=20, size=3,
                    color="#00FF66", fill="red")
```

```
# Class_a buildings

df$class_a = as.factor(df$class_a)
class_a <- ggplot(df, aes(x = class_a, y = Rent)) +
       geom_boxplot(colour = "lightgrey", fill = "#000066") + theme_classic() +
       labs(x = "class_a", y = "Rent",title = "class_a Vs Rent",
       subtitle = "All buildings") + theme(axis.text.x = element_text(
       face="bold",color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5)) +
       stat_summary(fun=median, geom="point", shape=20, size=3,
                    color="#00FF66", fill="red")

grid.arrange(leasing_rate, age, renovation, renovation_30,
             amenities, class_a, ncol = 3)
```



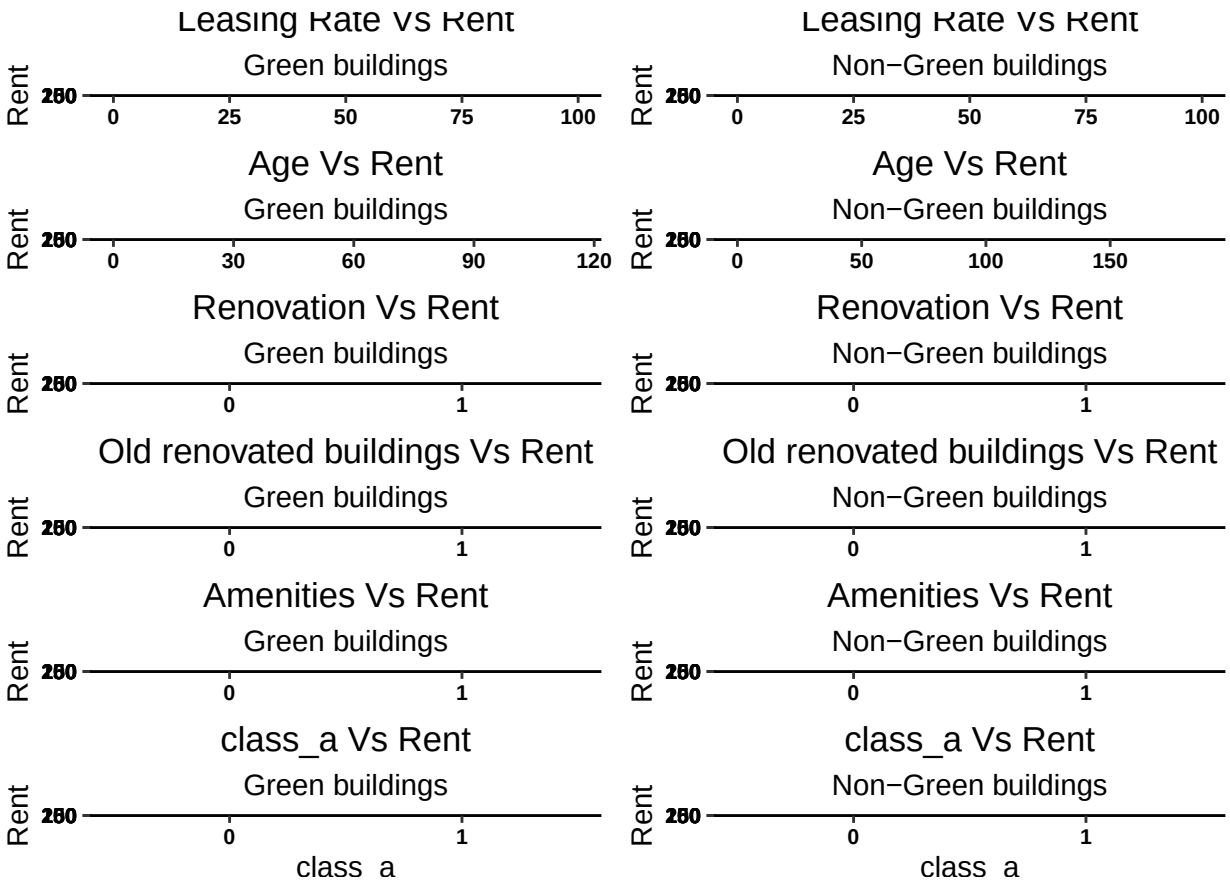

```
# Observations:

# Buildings with amenities and class_a buildings have a slightly higher rent
# Rent and Age do not have a visible relationship
# Leasing Rate and Rent seem to have a slightly positive relationship


# Looking at the green vs non green buildings separately
```

```r
knitr::opts_chunk$set(fig.width=12, fig.height=8)

green_buildings = subset(df, df$green_rating == 1)
non_green_buildings = subset(df, df$green_rating!= 1)

# Leasing_rate

# Green

leasing_rate_g = ggplot(green_buildings, aes(x=leasing_rate, y=Rent)) +
  theme_classic()+geom_point(colour = "darkolivegreen", size = 1.5,alpha= 0.5) +
  labs(x = "Leasing Rate", y = "Rent",title = "Leasing Rate Vs Rent",
       subtitle = "Green buildings") + ylim(0,250) + theme(axis.text.x =
       element_text(face="bold",color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),plot.subtitle =
       element_text(hjust = 0.5))

# Non Green

leasing_rate_ng = ggplot(non_green_buildings, aes(x=leasing_rate, y=Rent)) +
  theme_classic()+geom_point(colour = "darkolivegreen", size = 1.5,alpha= 0.5) +
  labs(x = "Leasing Rate", y = "Rent",title = "Leasing Rate Vs Rent",
       subtitle = "Non Green buildings") + ylim(0,250) + theme(axis.text.x =
       element_text(face="bold",color="black", size=8, angle=0), axis.text.y =
       element_text(face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5))

# Age

age_g = ggplot(green_buildings,aes(x = age,y = Rent)) +
  theme_classic()+geom_point(colour = "navyblue", size = 1.5,alpha = 0.5) +
  labs(x = "Age", y = "Rent",title = "Age Vs Rent",
       subtitle = "Green buildings") + ylim(0,250) + theme(axis.text.x =
       element_text(face="bold",color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5))

# Renovations

renovation_g <- ggplot(green_buildings, aes(x = renovated, y = Rent)) +
  geom_boxplot(colour = "grey", fill = "#CC9900") + ylim(0,250) +
  theme_classic() + labs(x = "Renovation(Yes:1| No:0)", y = "Rent",
       title = "Renovation Vs Rent", subtitle = "Green buildings") +
       theme(axis.text.x = element_text(face="bold",color="black",
       size=8, angle=0), axis.text.y = element_text(face="bold",
       color="black", size=8,    angle=0), plot.title =
       element_text(hjust = 0.5), plot.subtitle = element_text(hjust = 0.5))+
  stat_summary(fun=median, geom="point", shape=20, size=3, color="red",
       fill="red")
```

```
# Renovations in buildings older than 30 years

renovation_30_years_more = subset(green_buildings,green_buildings$age >=30)
renovation_30_g <- ggplot(renovation_30_years_more,
        aes(x = renovated, y = Rent)) + geom_boxplot(colour = "darkgrey",
        fill = "#33CC99") + theme_classic() + ylim(0,250) +
        labs(x = "Renovation(Yes:1| No:0)", y = "Rent",
        title = "Old renovated buildings Vs Rent",
        subtitle = "Green buildings") + theme(axis.text.x = element_text(
        face="bold",color="black", size=8, angle=0), axis.text.y = element_text(
        face="bold", color="black", size=8,    angle=0),
        plot.title = element_text(hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5))+
        stat_summary(fun=median, geom="point", shape=20,
                     size=3, color="#999900", fill="red")

# Amenities

amenities_g <- ggplot(green_buildings, aes(x = amenities, y = Rent)) +
  geom_boxplot(colour = "lightgrey", fill = "#000066") + theme_classic() +
  ylim(0,250) + labs(x = "Amenities", y = "Rent",title = "Amenities Vs Rent",
        subtitle = "Green buildings") + theme(axis.text.x = element_text(
        face="bold",color="black", size=8, angle=0), axis.text.y = element_text(
        face="bold", color="black", size=8,    angle=0),
        plot.title = element_text(hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5)) +
        stat_summary(fun=median, geom="point",
                     shape=20, size=3, color="#00FF66", fill="red")

# class_a buildings

class_a_g <- ggplot(green_buildings, aes(x = class_a, y = Rent)) +
  geom_boxplot(colour = "lightgrey", fill = "#000066") +
  theme_classic() + ylim(0,250) +  labs(x = "class_a", y = "Rent",
        title = "class_a Vs Rent",subtitle = "Green buildings") +
        theme(axis.text.x = element_text(face="bold",color="black", size=8,
        angle=0), axis.text.y = element_text(face="bold", color="black", size=8,
        angle=0), plot.title = element_text(hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5)) + stat_summary(fun=median,
        geom="point", shape=20, size=3, color="#00FF66", fill="red")

# Non-Green buildings

leasing_rate_ng = ggplot(non_green_buildings, aes(x=leasing_rate, y=Rent)) +
  theme_classic()+geom_point(colour = "darkolivegreen", size = 1.5) +
  labs(x = "Leasing Rate", y = "Rent",title = "Leasing Rate Vs Rent",
       subtitle = "Non-Green buildings") + theme(axis.text.x =
       element_text(face="bold",color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5))

# Age
```

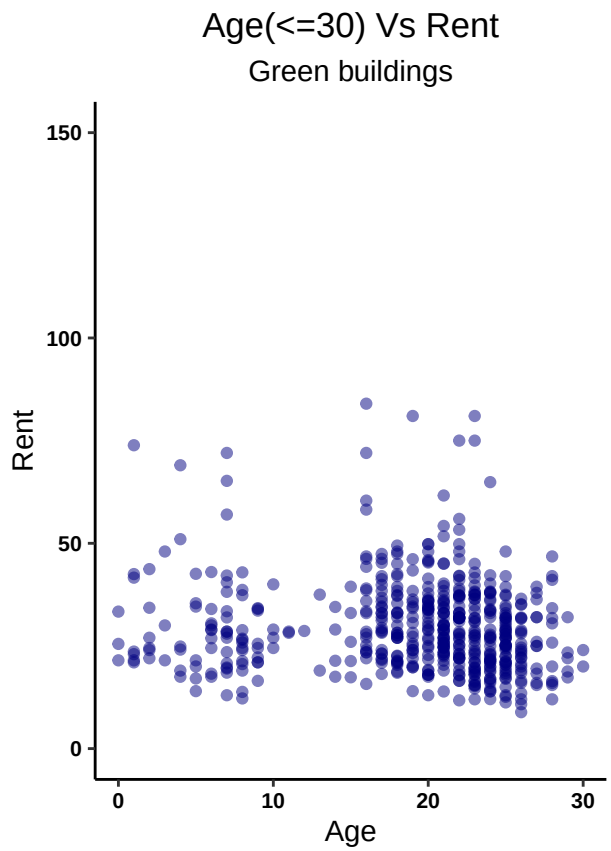
```
age_ng = ggplot(non_green_buildings,aes(x = age,y = Rent)) + geom_point() +
  theme_classic()+geom_point(colour = "navyblue", size = 1.5)+ labs(x = "Age",
  y = "Rent",title = "Age Vs Rent",subtitle = "Non-Green buildings") +
  theme(axis.text.x = element_text(face="bold",color="black", size=8, angle=0),
  axis.text.y = element_text(face="bold", color="black", size=8, angle=0),
  plot.title = element_text(hjust = 0.5),plot.subtitle =
  element_text(hjust = 0.5))

# Renovations

renovation_ng <- ggplot(non_green_buildings, aes(x = renovated, y = Rent)) +
  geom_boxplot(colour = "grey", fill = "#CC9900") + theme_classic() +
  labs(x = "Renovation(Yes:1| No:0)", y = "Rent",title = "Renovation Vs Rent",
       subtitle = "Non-Green buildings") +
  theme(axis.text.x = element_text(face="bold",
       color="black", size=8, angle=0),
       axis.text.y = element_text(face="bold",
       color="black", size=8,    angle=0),
       plot.title = element_text(hjust = 0.5),
       plot.subtitle = element_text(hjust = 0.5))+ stat_summary(fun=median,
       geom="point", shape=20, size=3, color="red", fill="red")

# Renovations in buildings older than 30 years

renovation_30_years_more = subset(non_green_buildings,
                                  non_green_buildings$age >=30)
renovation_30_ng <- ggplot(renovation_30_years_more, aes(x = renovated,
       y = Rent)) + geom_boxplot(colour = "darkgrey", fill = "#33CC99") +
  theme_classic() + labs(x = "Renovation(Yes:1| No:0)", y = "Rent",
       title = "Old renovated buildings Vs Rent", subtitle =
       "Non-Green buildings") + theme(axis.text.x = element_text(
        face="bold",color="black", size=8, angle=0), axis.text.y =
        element_text(face="bold", color="black", size=8, angle=0),plot.title =
        element_text(hjust = 0.5),plot.subtitle = element_text(hjust = 0.5))+
        stat_summary(fun=median, geom="point", shape=20, size=3,
                     color="#999900", fill="red")

# Amenities

amenities_ng <- ggplot(non_green_buildings, aes(x = amenities, y = Rent)) +
  geom_boxplot(colour = "lightgrey", fill = "#000066") + theme_classic() +
  labs(x = "Amenities", y = "Rent",title = "Amenities Vs Rent",subtitle =
         "Non-Green buildings") + theme(axis.text.x = element_text(face=
         "bold",color="black", size=8, angle=0), axis.text.y = element_text(
         face="bold", color="black", size=8,    angle=0),plot.title =
         element_text(hjust = 0.5),plot.subtitle = element_text(hjust = 0.5))+
  stat_summary(fun=median, geom="point", shape=20, size=3, color="#00FF66",
         fill="red")

# class_a buildings

class_a_ng <- ggplot(non_green_buildings, aes(x = class_a, y = Rent)) +
  geom_boxplot(colour = "lightgrey", fill = "#000066") + theme_classic() +
```

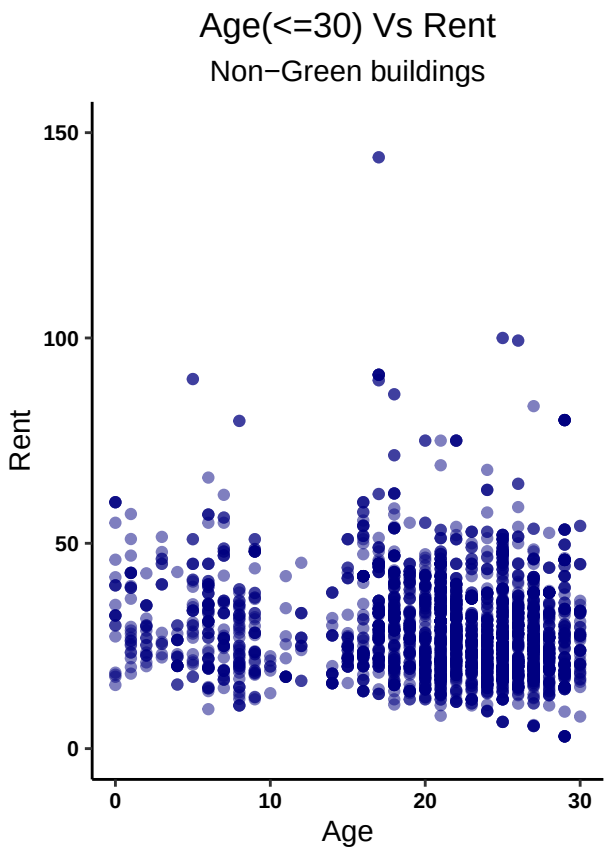
```
  labs(x = "class_a", y = "Rent",title = "class_a Vs Rent",
       subtitle = "Non-Green buildings") + theme(axis.text.x = element_text(
       face="bold",color="black", size=8, angle=0), axis.text.y = element_text(
       face="bold", color="black", size=8,    angle=0),plot.title = element_text(
       hjust = 0.5),plot.subtitle = element_text(hjust = 0.5))+
       stat_summary(fun=median, geom="point", shape=20, size=3,
       color="#00FF66", fill="red")
grid.arrange(leasing_rate_g,
             leasing_rate_ng,
             age_g,age_ng,
             renovation_g,
             renovation_ng,
             renovation_30_g,
             renovation_30_ng,
             amenities_g,
             amenities_ng,
             class_a_g,
             class_a_ng,
             ncol = 2)
```




```
# Observations:

# Older green buildings seem to charge higher rents when renovated
# There is not a clearly visible variable that impacts the distribution of rent
# even after splitting for green vs non-green
```

```
# Diving deep into Age

green_buildings_by_age = subset(df,
                      df$green_rating == 1 & df$age <= 30 & df$net ==0)
non_green_buildings_by_age = subset(df,
                      df$green_rating!= 1 & df$age <= 30 & df$net ==0)

# Age plots and rent

rent_g_by_age = ggplot(green_buildings_by_age,aes(x = age,y = Rent)) +
  ylim(0,150) + theme_classic()+geom_point(colour = "navyblue", size = 1.5,
  alpha = 0.5)+ labs(x = "Age", y = "Rent", title = "Age(<=30) Vs Rent",
  subtitle = "Green buildings") + theme(axis.text.x = element_text(face="bold",
  color="black", size=8, angle=0), axis.text.y = element_text(face="bold",
  color="black", size=8, angle=0),plot.title = element_text(hjust = 0.5),
  plot.subtitle = element_text(hjust = 0.5))

rent_ng_by_age = ggplot(non_green_buildings_by_age,aes(x = age,y = Rent)) +
  ylim(0,150) + theme_classic()+geom_point(colour = "navyblue", size = 1.5,
  alpha = 0.5)+ labs(x = "Age", y = "Rent",title = "Age(<=30) Vs Rent",
  subtitle = "Non-Green buildings") + theme(axis.text.x = element_text(
  face="bold",color="black", size=8, angle=0), axis.text.y = element_text(
  face="bold", color="black", size=8, angle=0),plot.title = element_text(
  hjust = 0.5),plot.subtitle = element_text(hjust = 0.5))

grid.arrange(rent_g_by_age,rent_ng_by_age,ncol = 2)
```






```
print(paste("Median rent of green buildings less than 30 years of age:",
            median(green_buildings_by_age$Rent)))
```

```
## [1] "Median rent of green buildings less than 30 years of age: 28"
```

```
print(paste("Median rent of non - green buildings less than 30 years of age:",
            median(non_green_buildings_by_age$Rent)))
```

```
## [1] "Median rent of non - green buildings less than 30 years of age: 27"
```

```
# Observations:

# We see that even the age is not a primary factor since rent of green buildings
# is just higher across ages as well.

# After diving into all the separate variables, and also considering the green vs
# non- green scenario, it is evident that people are willing to pay more rent
# based on the green building parameter

# Estimating Returns

# Consider a local market cluster

hist(unique(df$cluster_rent),main = paste("Histogram of Cluster rent"),xlab = 'Rent')
abline(v = median(unique(df$cluster_rent)), col="red", lwd=3, lty=2)
```


```
# Calculation the no. of local markets where rent for green building is greater
# than median cluster (Conidering median as it is more robust to outliers)

cluster_quants = ddply(df,.(cluster), function(x)quantile(x$Rent))[c('cluster','50%')]
temp = merge(green_buildings,cluster_quants,by = 'cluster')
more_rent_green = subset(temp,temp$'Rent' >= temp$'50%')
less_rent_green = subset(temp,temp$'Rent' < temp$'50%')

# Observations:
# Green building rent > Median rent -> for more than 75% of local markets

# If we consider the mean of difference bw green and median local market's rent,
# we see that green buildings get ~$3 more than non-green

# Adjusting the estimates of the stats guru, by 0.4 , we can see that an extra
# $750,000 revenue can be earned by building a green building.

# Based on the extra revenue, we can recuperate the costs in 6.66 years and
# even with 90% occupancy as is evident from data, the builder can start earning
# profits after 7.4 years
```

Visual story telling part 2: Capital Metro data

Portfolio Modeling

```
library(mosaic)
library(quantmod)
library(foreach)
```

Low Risk ETFs : All Fixed Income ETFs - We are first going to create a low risk portfolio. For this purpose, we are going to select three specific type of ETFs:

USMV: Consists of US stocks with less risk. The Expense Ratio for this ETF is extremely low (about 15 cents for a $100 investment) More than 25% of this fund is exposed to Information Technology stocks which has grown almost similarly to the S&P index. It also has heavy exposure to sectors like Healthcare and Telecommunications which are not traditionally volatile.

EFAV: This ETF enables us to achieve some geographic diversification as it has exposure to Europe and Asia. The Net Expense ratio is 0.20 for this ETF. It has exposure to Healthcare and Consumer Staples, again two non-volatile sectors.

EEMV: We will achieve further geographic diversity as this ETF has holdings from emerging markets like China, India and Taiwan. This has exposure to the Financial Sector and will help us in diversifying away from the Healthcare sector.

```
## Suppress some uselesss warnings
defaultW <- getOption("warn")
options(warn = -1)

# Import a few stocks
low_risk_stocks = c("USMV", "EFAV","EEMV")
quantmod::getSymbols(low_risk_stocks,from ="2016-08-01",to = Sys.Date(),)
```

```
## [1] "USMV" "EFAV" "EEMV"
```

```
# Adjust for splits and dividends
USMVa = quantmod::adjustOHLC(USMV)
EFAVa = quantmod::adjustOHLC(EFAV)
EEMVa = quantmod::adjustOHLC(EEMV)
```

Let us now try to find out the volatility of these stocks.

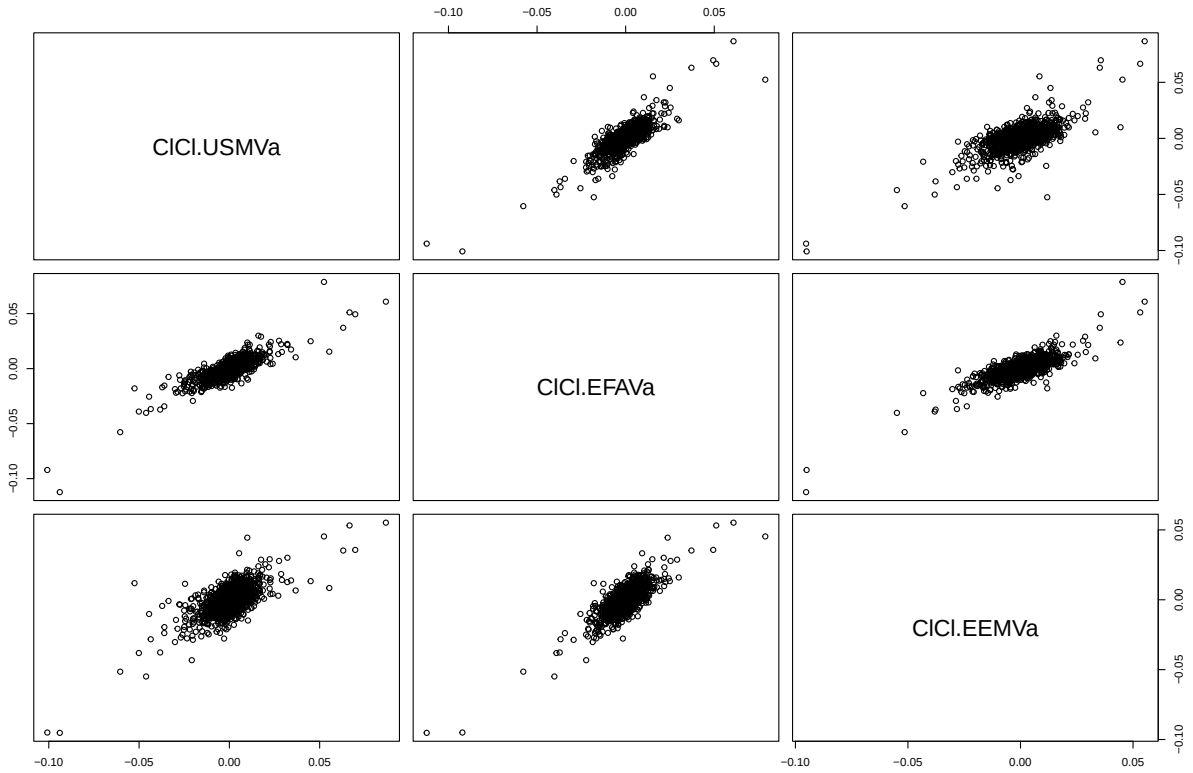
```
all_returns = cbind(ClCl(USMVa),
                    ClCl(EFAVa),
                    ClCl(EEMVa))
all_returns = as.matrix(na.omit(all_returns))
head(all_returns)
```

```
##              ClCl.USMVa    ClCl.EFAVa   ClCl.EEMVa
## 2016-08-02 -0.004471870  0.0000000000 -0.004709872
## 2016-08-03 -0.007486588 -0.0041408901  0.002649990
## 2016-08-04  0.003017220 -0.0011879122  0.002643005
```

```
## 2016-08-05  0.003008143  0.0001486024  0.007154980
## 2016-08-08 -0.002570673 -0.0031217335  0.005234586
## 2016-08-09  0.002147745  0.0062631228  0.004649433
```

We can plot some scatter plots to check if there is a strong relationship between these 3 ETFs.

```
## There is not very significant linear relationship between these ETFs
pairs(all_returns)
```

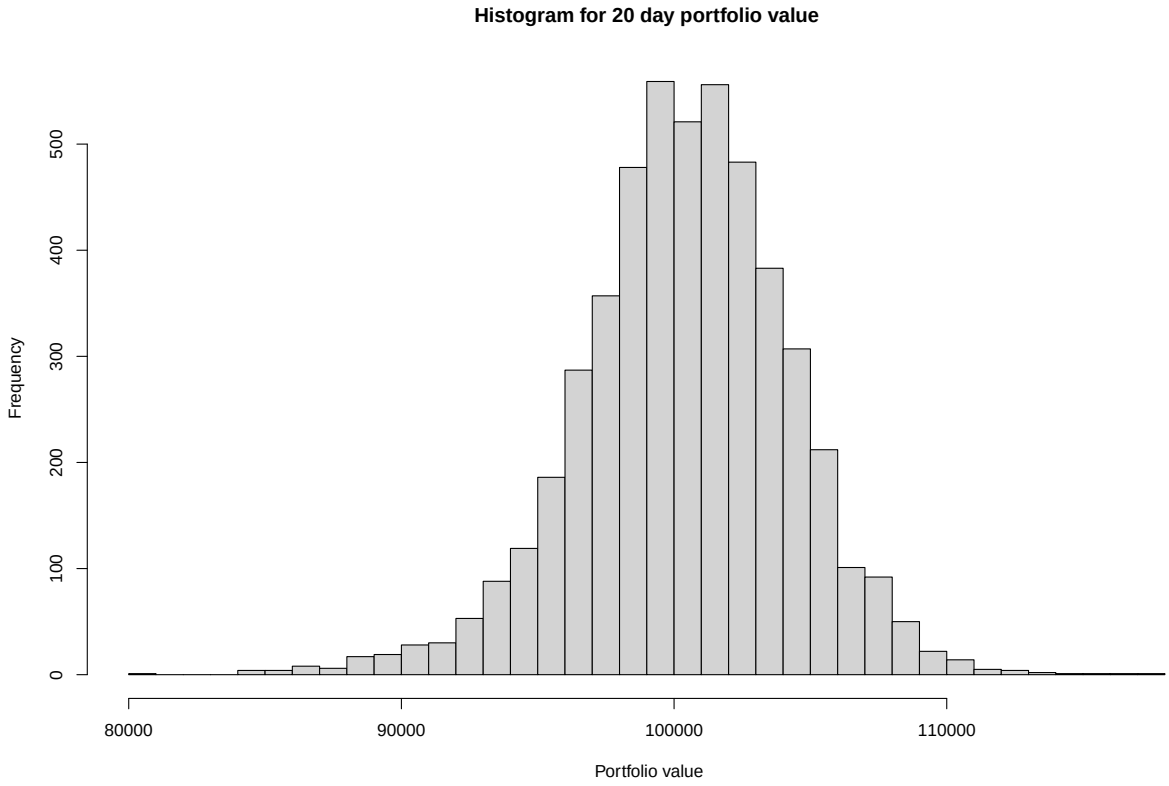



```
## We will apportion our total wealth in the ratio 25:35:40, putting more weight on the EEMVa ETF that
set.seed(0)
# Now simulate many different possible futures
# just repeating the above block thousands of times
initial_wealth = 100000
sim1 = foreach(i=1:5000, .combine='rbind') %do% {
  total_wealth = initial_wealth
  weights = c(0.25, 0.35, 0.40)
  holdings = weights * total_wealth
  n_days = 20
  wealthtracker = rep(0, n_days)
  for(today in 1:n_days)
    {
    return.today = resample(all_returns, 1, orig.ids=FALSE)
    holdings = holdings + holdings*return.today
    total_wealth = sum(holdings)
    wealthtracker[today] = total_wealth
```

```
    holdings = weights * total_wealth
  }
  wealthtracker
}
```

Let's look at the distribution plot by plotting a histogram

```
# Let's look at the distribution of total holdings value at the end of 20 days

hist(sim1[,20], 30, main = "Histogram for 20 day portfolio value", xlab = " Portfolio value")
```




```
# 5% VAR
quantile(sim1[,20]- initial_wealth, prob=0.05)
```

```
##        5%
## -6041.996
```

High Risk ETFs : All Equity ETFs We shall take all Equity ETFs for this purpose.

We will follow the same strategy as above for diversifying our portfolio.

AAXJ: This is an equity ETF with heavy exposure to emerging markets like China, India, Taiwan, Singapore, etc. It has very a diverse sector and industry composition ranging from E-Commerce to Electronics

BBEU: This is an extremely volatile fund. The returns on this fund has been very good over the last couple years. This fund has heavy exposure to Europe and will improve our portfolio diversification as it

has exposure to sectors like Healthcare and Consumer Staples. Moreover, this fund is mostly concentrated into healthcare and consumer staple that will add industry diversity to our portfolio

XLF: This fund focuses on the Financial and Real Estate behemoths of the US.

```
## Suppress some uselesss warnings
defaultW <- getOption("warn")
options(warn = -1)

# Import a few stocks
high_risk_stocks = c("AAXJ", "BBEU","XLF")
quantmod::getSymbols(high_risk_stocks,from ="2016-08-01",to = Sys.Date(),)
```

```
## [1] "AAXJ" "BBEU" "XLF"
```

```
# Adjust for splits and dividends
AAXJa = quantmod::adjustOHLC(AAXJ)
BBEUa = quantmod::adjustOHLC(BBEU)
XLFa = quantmod::adjustOHLC(XLF)
```

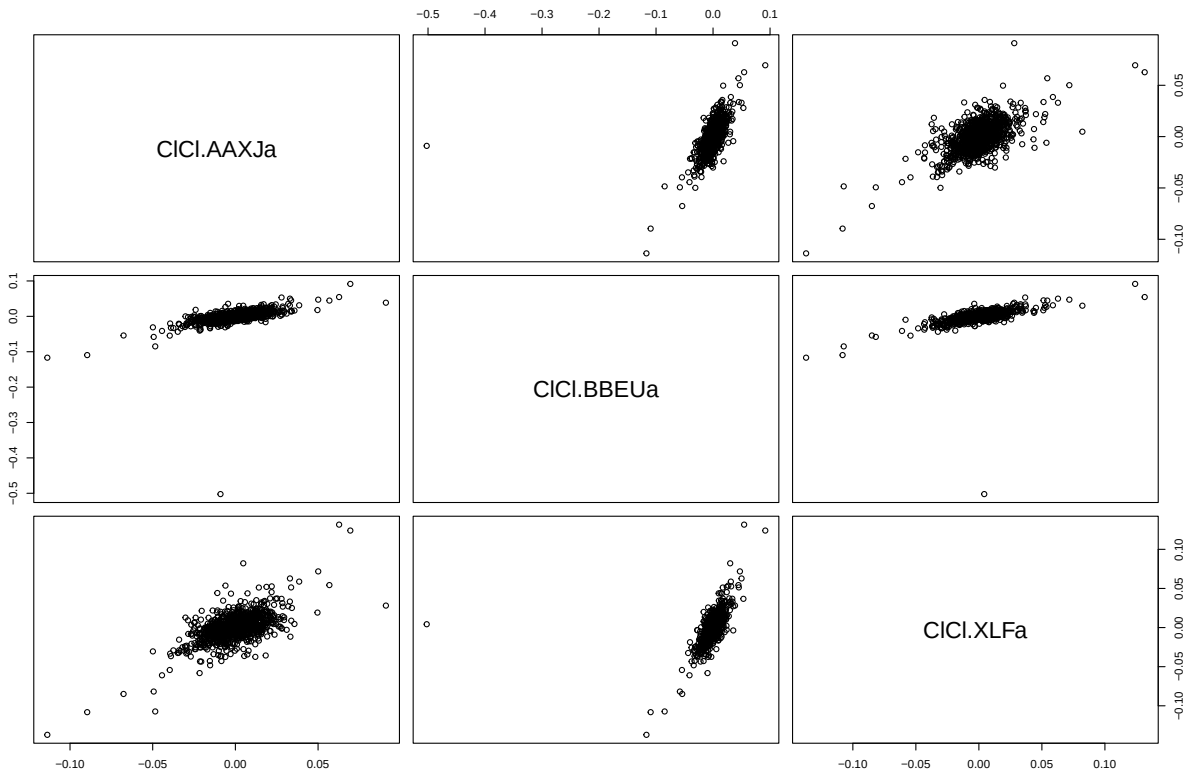
Let's now try to look at the volatility of these stocks

```
all_returns = cbind(ClCl(AAXJa),
                    ClCl(BBEUa),
                    ClCl(XLFa))
all_returns = as.matrix(na.omit(all_returns))
head(all_returns)
```

```
##              ClCl.AAXJa   ClCl.BBEUa    ClCl.XLFa
## 2018-06-19 -0.013058860  0.000000000 -0.002552881
## 2018-06-20  0.003403213 -0.004446281 -0.002559378
## 2018-06-21 -0.017094044 -0.008526147 -0.002932551
## 2018-06-22  0.009247840  0.000000000 -0.004779448
## 2018-06-25 -0.015043845  0.001760831 -0.010712929
## 2018-06-26 -0.002221550 -0.004210399 -0.003360717
```

Let's see is there is a strong relationship between these ETFs.

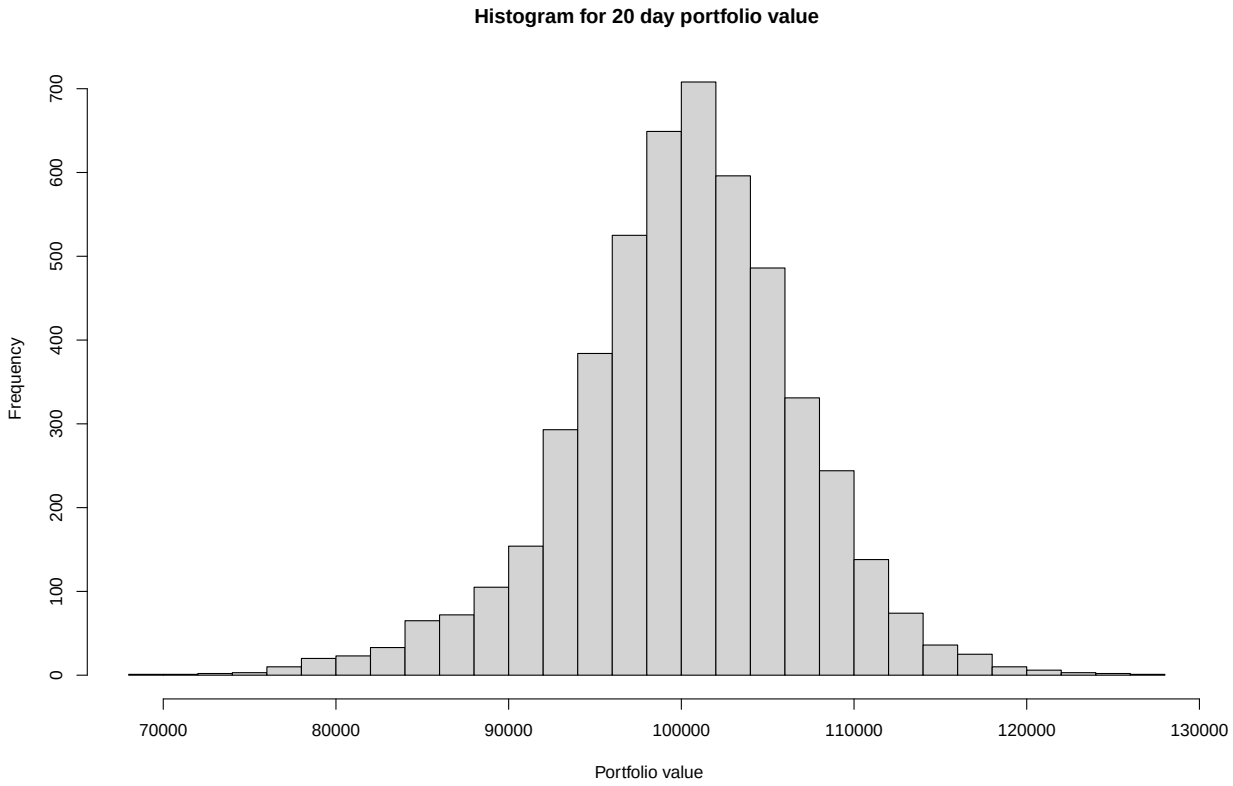
```
## There is not very significant linear relationship between these ETFs
pairs(all_returns)
```




```
## We will apportion our total wealth in the ratio 25:35:40, putting more weight on the AAXJ ETF that i
set.seed(0)
# Now simulate many different possible futures
# just repeating the above block thousands of times
initial_wealth = 100000
sim2 = foreach(i=1:5000, .combine='rbind') %do% {
  total_wealth = initial_wealth
  weights = c(0.25, 0.35, 0.40)
  holdings = weights * total_wealth
  n_days = 20
  wealthtracker = rep(0, n_days)
  for(today in 1:n_days)
    {
    return.today = resample(all_returns, 1, orig.ids=FALSE)
    holdings = holdings + holdings*return.today
    total_wealth = sum(holdings)
    wealthtracker[today] = total_wealth
    holdings = weights * total_wealth
  }
  wealthtracker
}
```

Let's look at the distribution plot by plotting a histogram.

```
# Let's look at the distribution of total holdings value at the end of 20 days

hist(sim2[,20], 30, main = "Histogram for 20 day portfolio value", xlab = " Portfolio value")
```




```
# 5% VAR
quantile(sim2[,20]- initial_wealth, prob=0.05)
```

```
##        5%
## -11476.36
```

Balanced ETFs : Mix of Equity and Fixed Income our strategy for this will be taking 3 funds:

AOR : This fund has a good mix of bonds and global stocks.

AOM: This fund is pretty similar to AOM

IYLD: This fund consists of 60% bonds, 20% equity. It is a good addition to a balanced portfolio.

```
## Suppress some uselesss warnings
defaultW <- getOption("warn")
options(warn = -1)

# Import a few stocks
balanced_efts = c("AOR", "AOM","IYLD")
quantmod::getSymbols(balanced_efts,from ="2016-08-01",to = Sys.Date(),)
```

```
## [1] "AOR"  "AOM"  "IYLD"
```

```
# Adjust for splits and dividends
AORa = quantmod::adjustOHLC(AOR)
AOMa = quantmod::adjustOHLC(AOM)
IYLDa = quantmod::adjustOHLC(IYLD)
```

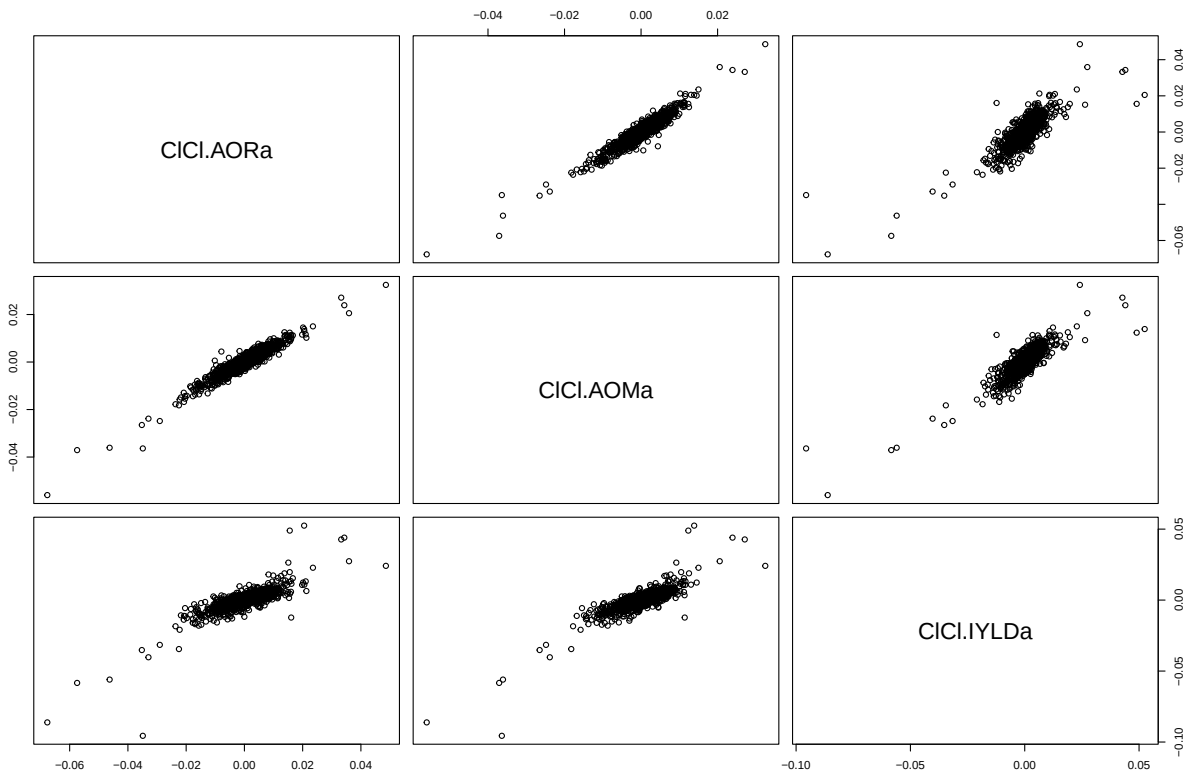
Let us now try to look at the volatility of these stocks.

```
all_returns = cbind(ClCl(AORa),
                    ClCl(AOMa),
                    ClCl(IYLDa))
all_returns = as.matrix(na.omit(all_returns))
head(all_returns)
```

```
##                ClCl.AORa    ClCl.AOMa   ClCl.IYLDa
## 2016-08-02 -0.0056469433 -0.006419313 -0.003134121
## 2016-08-03  0.0000000000  0.002528118  0.003224506
## 2016-08-04  0.0034567654  0.000000000  0.004017718
## 2016-08-05  0.0036909942  0.003922752  0.001200480
## 2016-08-08  0.0007354498 -0.001116411  0.001998401
## 2016-08-09  0.0034296668  0.004191059  0.005584324
```

Let us see is there is a strong relationship between these ETFs by plotting a few scatter plots.

```
## There is not very significant linear relationship between these ETFs
pairs(all_returns)
```

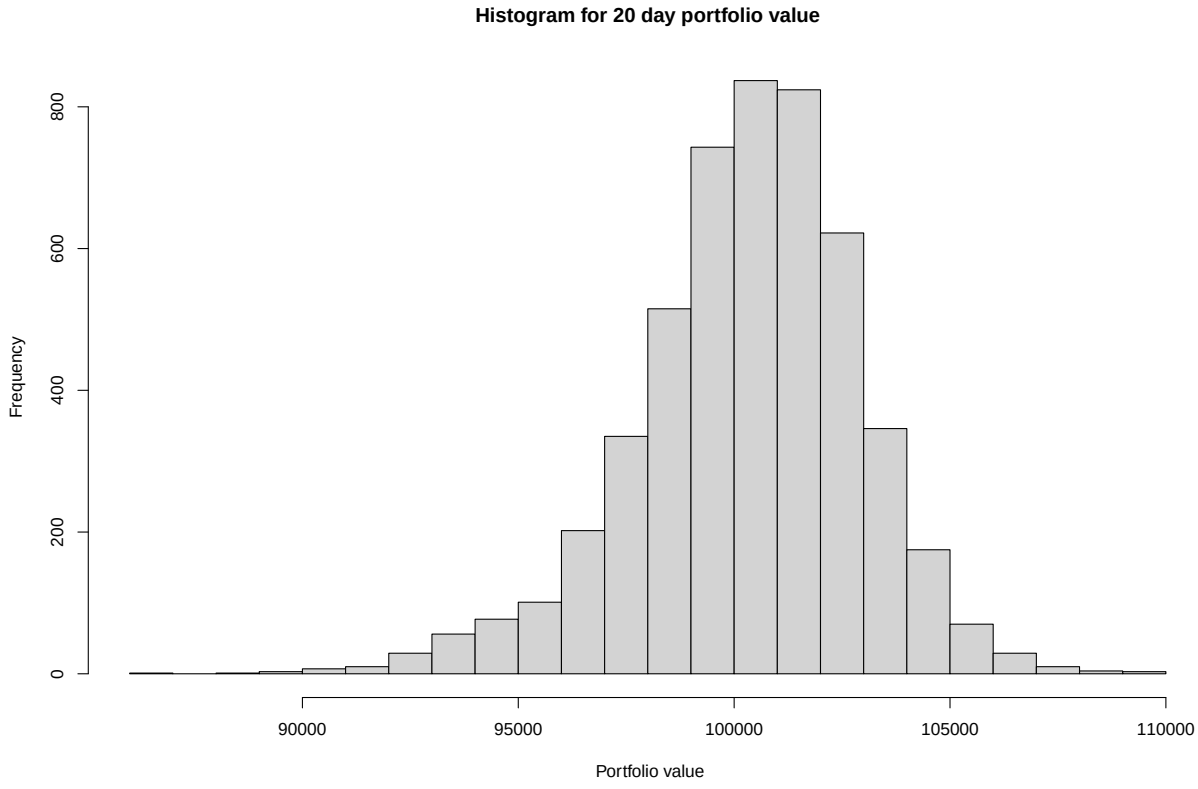



```
## We will apportion our total wealth in the ratio 25:35:40, putting more weight on the AAXJ ETF that i
set.seed(0)
# Now simulate many different possible futures
# just repeating the above block thousands of times
initial_wealth = 100000
```

```
sim3 = foreach(i=1:5000, .combine='rbind') %do% {
  total_wealth = initial_wealth
  weights = c(0.25, 0.35, 0.40)
  holdings = weights * total_wealth
  n_days = 20
  wealthtracker = rep(0, n_days)
  for(today in 1:n_days)
    {
    return.today = resample(all_returns, 1, orig.ids=FALSE)
    holdings = holdings + holdings*return.today
    total_wealth = sum(holdings)
    wealthtracker[today] = total_wealth
    holdings = weights * total_wealth
  }
  wealthtracker
}
```

Let us look at the distribution plot by plotting a histogram.

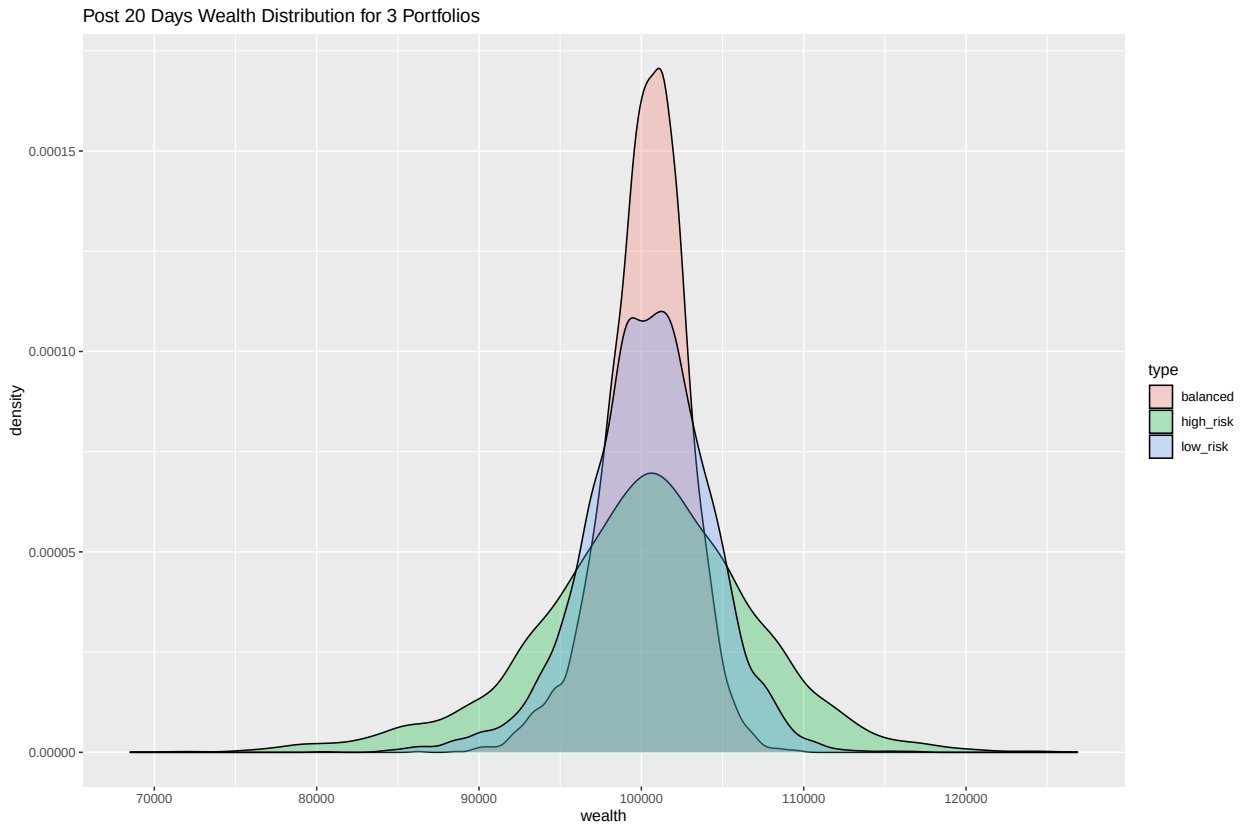
```
# Let's look at the distribution of total holdings value at the end of 20 days

hist(sim3[,20], 30, main = "Histogram for 20 day portfolio value", xlab = " Portfolio value")
```




```
# 5% VAR
quantile(sim3[,20]- initial_wealth, prob=0.05)
```

```
##        5%
## -4223.054
```

```
library(ggplot2)
library(dplyr)

#Sample data




dat1 <- data.frame(wealth = sim1[,20],
                   type = 'low_risk')
dat2 <- data.frame(wealth = sim2[,20],
                   type = 'high_risk')
dat3 <- data.frame(wealth = sim3[,20],
                   type = 'balanced')

hist_df = rbind(dat1,dat2,dat3)

a <- ggplot(hist_df, aes(x = wealth))
a + geom_density(aes(fill = type), alpha=0.3) + ggtitle('Post 20 Days Wealth Distribution for 3 Portfoli
```

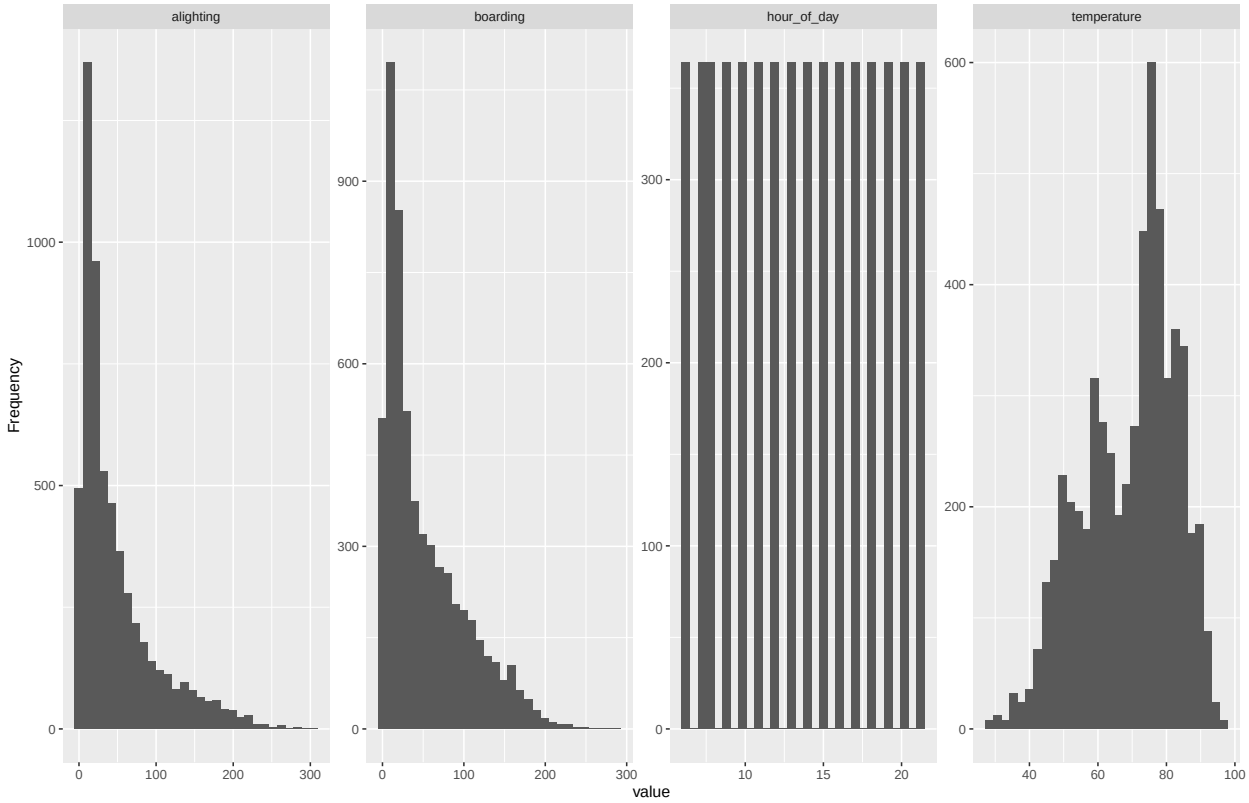


The density plot for wealth after 20 days is mostly in line with our expectations. The high risk portfolio has more variance as expected and has highest VAR at about 5%. Ideally, the balanced portfolio's variance should have lied between the high and low risk portfolios but here we some deviation from expected behavior.

This could be due to the EFT selections that we have made ofr building our portfolios.

Visual story telling part 2: Capital Metro data

```
library(gridExtra)
library(ggplot2)
# library(dplyr)
library(tidyverse)
library(DataExplorer)

#detach(package:plyr,unload=TRUE)

metro <- read.csv("capmetro_UT.csv")

# Looking at some distributions

ncols <- dplyr::select_if(metro, is.numeric)
plot_histogram(ncols)
```

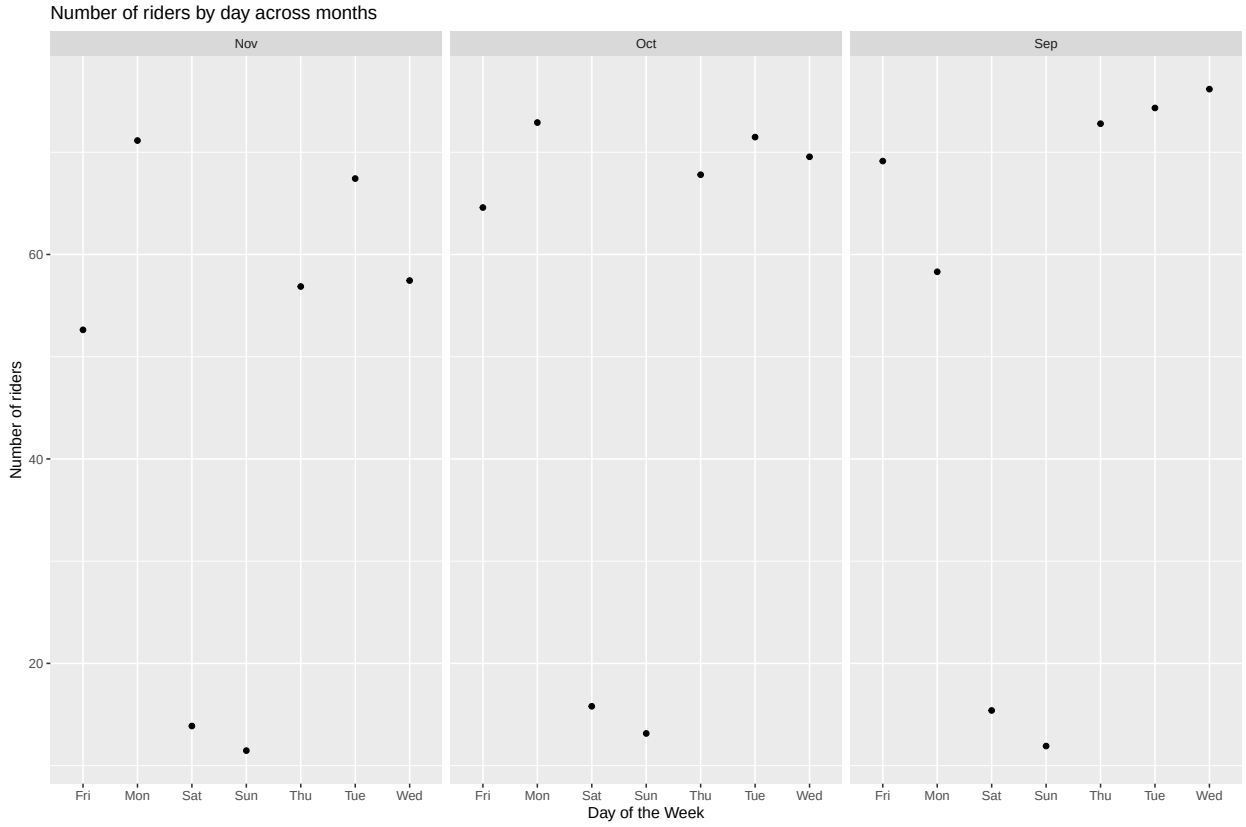



```
# Diving into riders analysis

library(tidyverse)

r1 = metro %>%
              group_by(hour_of_day) %>%
                dplyr::summarize(riders = mean(boarding))
```

```
r2 = metro %>%
             group_by(hour_of_day) %>%
                dplyr::summarize(riders = mean(alighting))

plot1 = ggplot(r1) + geom_line(aes(x=hour_of_day, y=riders)) +
                                  ggtitle("Number of people boarding")

plot2 = ggplot(r2) + geom_line(aes(x=hour_of_day, y=riders)) +
                                  ggtitle("Number of people alighting")

# grid.arrange(r1, r2, nrow = 1)

r3 = metro %>%
            group_by(day_of_week,month) %>%
              dplyr::summarize(riders = mean(boarding))
```

```
## `summarise()` has grouped output by 'day_of_week'. You can override using the
## `.groups` argument.
```

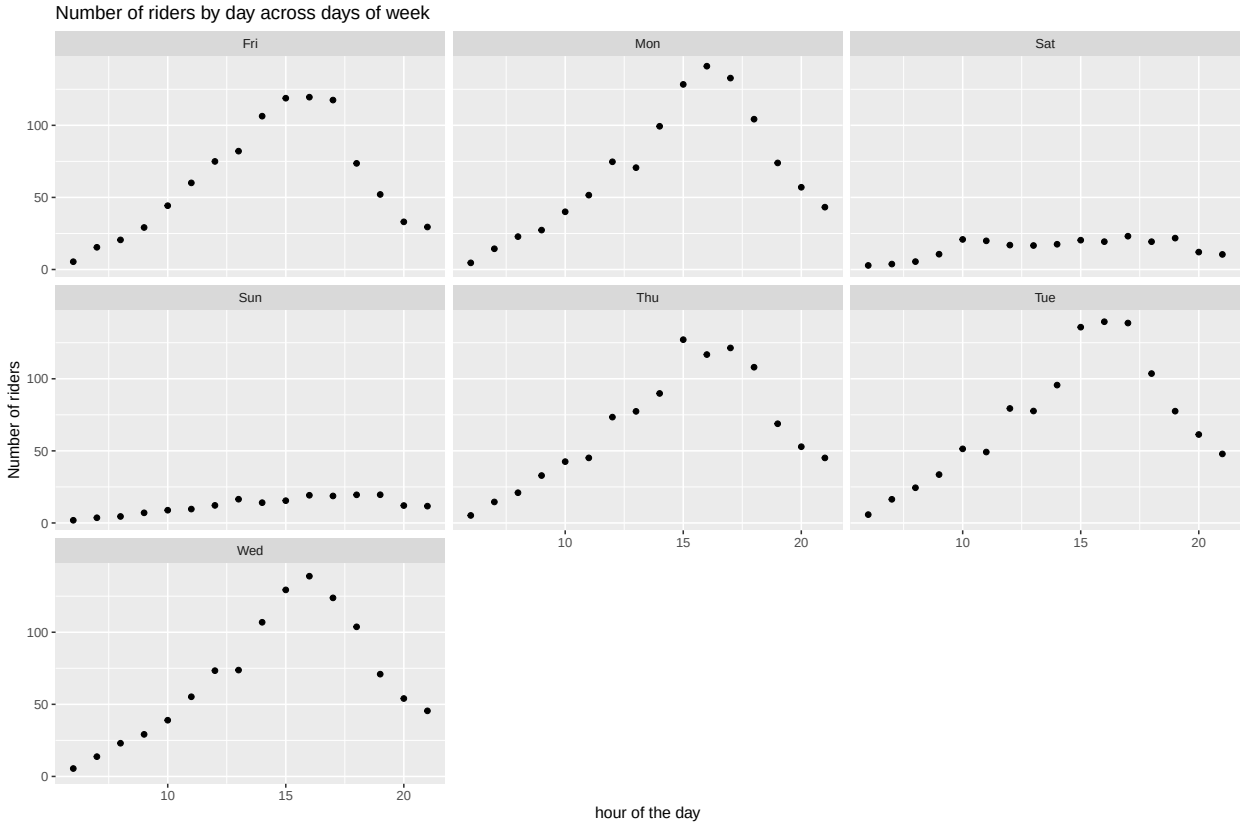
```
ggplot(r3) + geom_point(aes(x=day_of_week, y=riders)) + facet_wrap(~month) +
            labs(x="Day of the Week", y="Number of riders",
                 title="Number of riders by day across months")
```




```
r4 = metro %>%
               group_by(hour_of_day, day_of_week) %>%
                 dplyr::summarize(riders = mean(boarding))
```

```
## `summarise()` has grouped output by 'hour_of_day'. You can override using the
## `.groups` argument.
```

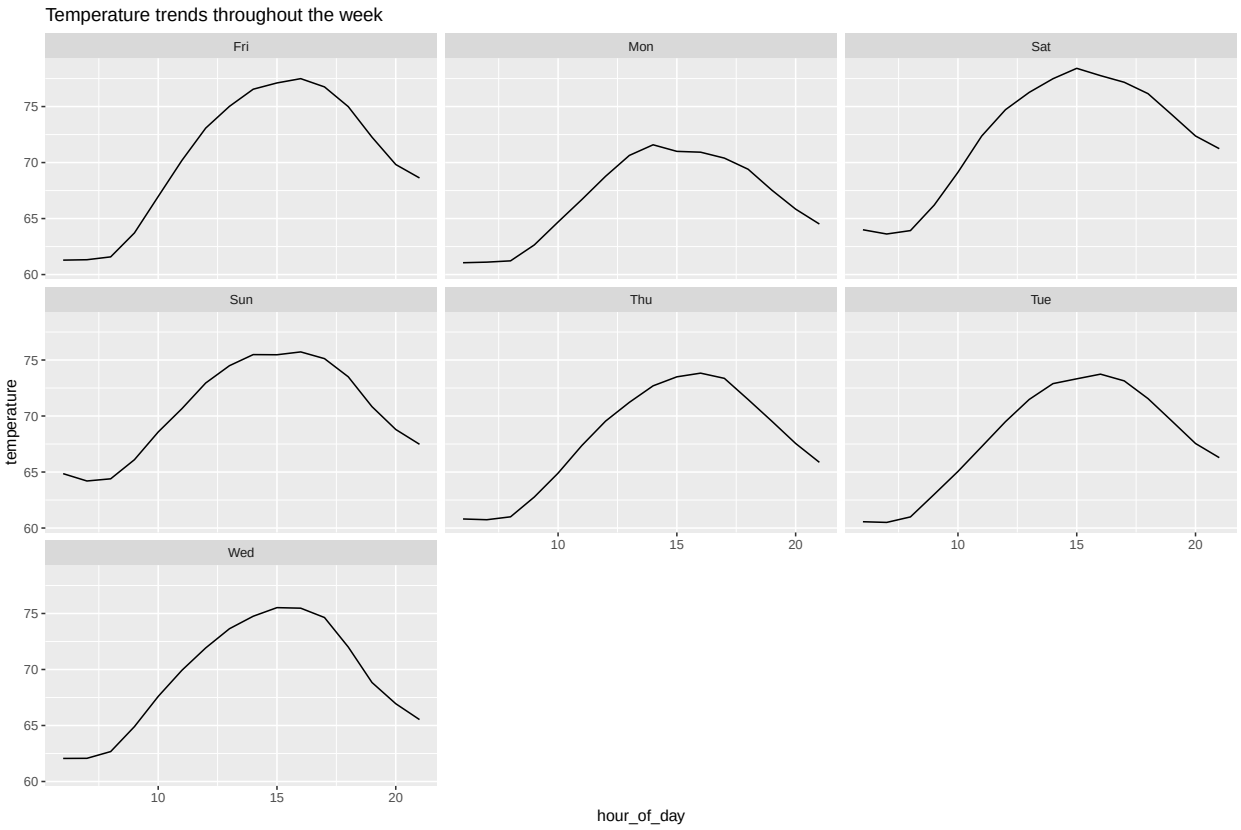
```
ggplot(r4) + geom_point(aes(x=hour_of_day, y=riders)) +
             facet_wrap(~day_of_week) + labs(x="hour of the day",
  y="Number of riders", title="Number of riders by day across days of week")
```




```
r5 = metro %>%
        group_by(day_of_week, hour_of_day) %>%
            dplyr::summarize(temperature = mean(temperature))
```

```
## `summarise()` has grouped output by 'day_of_week'. You can override using the
## `.groups` argument.
```

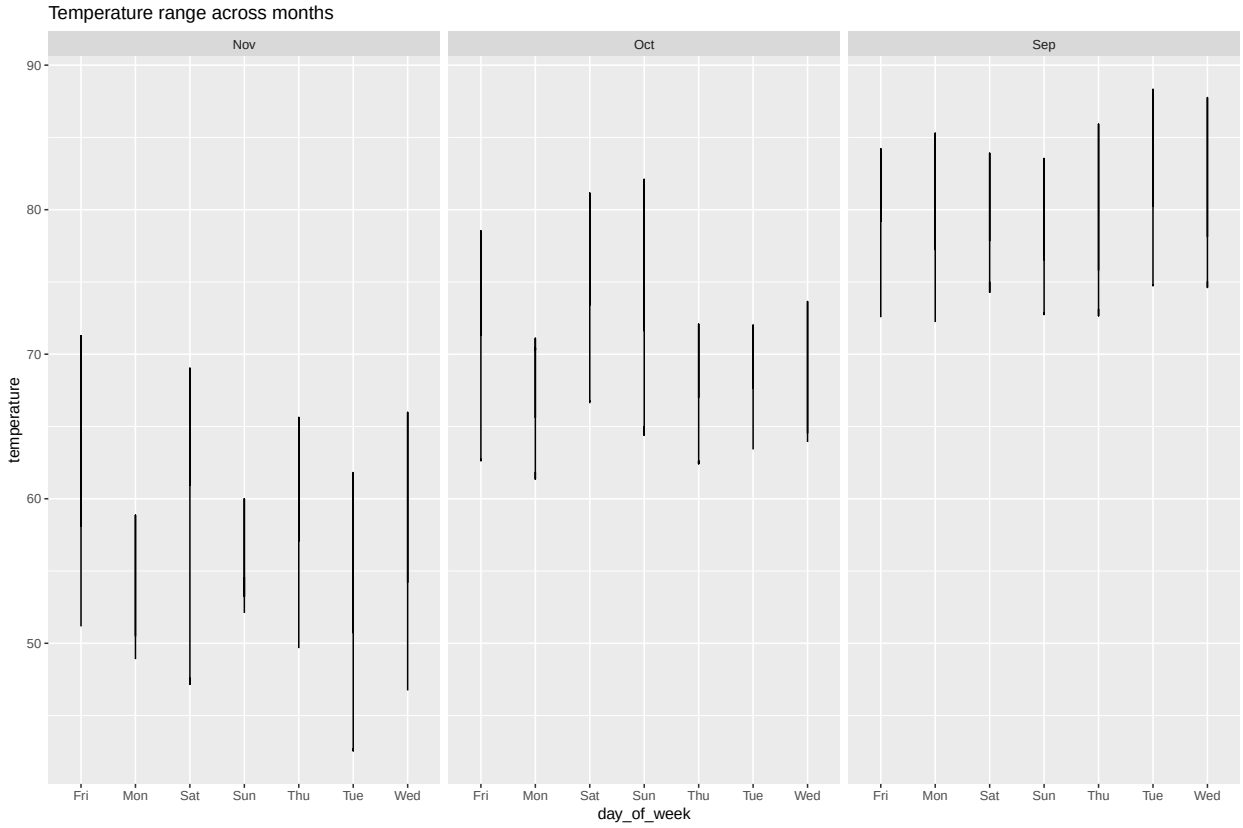
```
ggplot(r5) + geom_line(aes(x=hour_of_day, y=temperature)) +
    ggtitle("Temperature trends throughout the week") + facet_wrap(~day_of_week)
```




```
r6 = metro %>%
        group_by(day_of_week, hour_of_day,month) %>%
          dplyr::summarize(temperature = mean(temperature))
```

```
## `summarise()` has grouped output by 'day_of_week', 'hour_of_day'. You can
## override using the `.groups` argument.
```

```
ggplot(r6) +
  geom_line(aes(x=day_of_week, y=temperature)) +
      ggtitle("Temperature range across months") +
          facet_wrap(~month)
```



Clustering and PCA

```
library(ggplot2)
library(ClusterR)
```

```
## Loading required package: gtools
```

```
##
## Attaching package: 'gtools'
```

```
## The following object is masked from 'package:mosaic':
##
##     logit
```

```
library(foreach)
library(mosaic)

wine = read.csv('wine.csv', header=TRUE)

summary(wine)
```

```
##  fixed.acidity    volatile.acidity  citric.acid     residual.sugar
```

```
##  Min.   : 3.800   Min.   :0.0800   Min.   :0.0000   Min.   : 0.600
##  1st Qu.: 6.400   1st Qu.:0.2300   1st Qu.:0.2500   1st Qu.: 1.800
##  Median : 7.000   Median :0.2900   Median :0.3100   Median : 3.000
##  Mean   : 7.215   Mean   :0.3397   Mean   :0.3186   Mean   : 5.443
##  3rd Qu.: 7.700   3rd Qu.:0.4000   3rd Qu.:0.3900   3rd Qu.: 8.100
##  Max.   :15.900   Max.   :1.5800   Max.   :1.6600   Max.   :65.800
##    chlorides       free.sulfur.dioxide total.sulfur.dioxide    density
##  Min.   :0.00900   Min.   :  1.00      Min.   :  6.0        Min.   :0.9871
##  1st Qu.:0.03800   1st Qu.: 17.00      1st Qu.: 77.0        1st Qu.:0.9923
##  Median :0.04700   Median : 29.00      Median :118.0        Median :0.9949
##  Mean   :0.05603   Mean   : 30.53      Mean   :115.7        Mean   :0.9947
##  3rd Qu.:0.06500   3rd Qu.: 41.00      3rd Qu.:156.0        3rd Qu.:0.9970
##  Max.   :0.61100   Max.   :289.00      Max.   :440.0        Max.   :1.0390
##        pH          sulphates         alcohol         quality
##  Min.   :2.720   Min.   :0.2200   Min.   : 8.00   Min.   :3.000
##  1st Qu.:3.110   1st Qu.:0.4300   1st Qu.: 9.50   1st Qu.:5.000
##  Median :3.210   Median :0.5100   Median :10.30   Median :6.000
##  Mean   :3.219   Mean   :0.5313   Mean   :10.49   Mean   :5.818
##  3rd Qu.:3.320   3rd Qu.:0.6000   3rd Qu.:11.30   3rd Qu.:6.000
##  Max.   :4.010   Max.   :2.0000   Max.   :14.90   Max.   :9.000
##     color
##  Length:6497
##  Class :character
##  Mode  :character
##
##
##
```

```
# Center and scale the data

X = wine[,-(12:13)]
X = scale(X, center=TRUE, scale=TRUE)

# trying 2 Prinicipal Components

wine$Good_Quality_Wine<-ifelse(wine$quality>5,"Good Quality","Bad Quality")
dim(wine)
```

```
## [1] 6497   14
```

```
pca1 = prcomp(wine[,1:12], scale. = TRUE, rank = 2)
summary(pca1)
```

```
## Importance of first k=2 (out of 12) components:
##                           PC1    PC2
## Standard deviation     1.7440 1.6278
## Proportion of Variance 0.2535 0.2208
## Cumulative Proportion  0.2535 0.4743
```

```
loadings = pca1$rotation
scores = pca1$x
```

```
plot1<-qplot(scores[,1], scores[,2], color=wine$color,
             xlab='Component 1', ylab='Component 2')
plot2<-qplot(scores[,1], scores[,2], color=wine$Good_Quality_Wine,
             xlab='Component 1', ylab='Component 2')
grid.arrange(plot1, plot2, nrow = 2)
```


```
# trying 2 Clusters

wine$good<-ifelse(wine$quality>5,"blue","red")
wine$color2<-ifelse(wine$color=="red","red","blue")

X = wine[,1:12]
X = scale(X, center=TRUE, scale=TRUE)

mu = attr(X,"scaled:center")
sigma = attr(X,"scaled:scale")

clust1 = kmeans(X, 2, nstart=25)
clust1$center
```

```
##   fixed.acidity volatile.acidity citric.acid residual.sugar  chlorides
## 1    -0.2833598       -0.4002457   0.1163397      0.2036791 -0.3133076
## 2     0.8203503        1.1587448  -0.3368131     -0.5896682  0.9070517
##   free.sulfur.dioxide total.sulfur.dioxide    density         pH  sulphates
## 1           0.2875184            0.4055994 -0.2316456 -0.1918762 -0.2847052
## 2          -0.8323898           -1.1742444  0.6706333  0.5554976  0.8242456
```

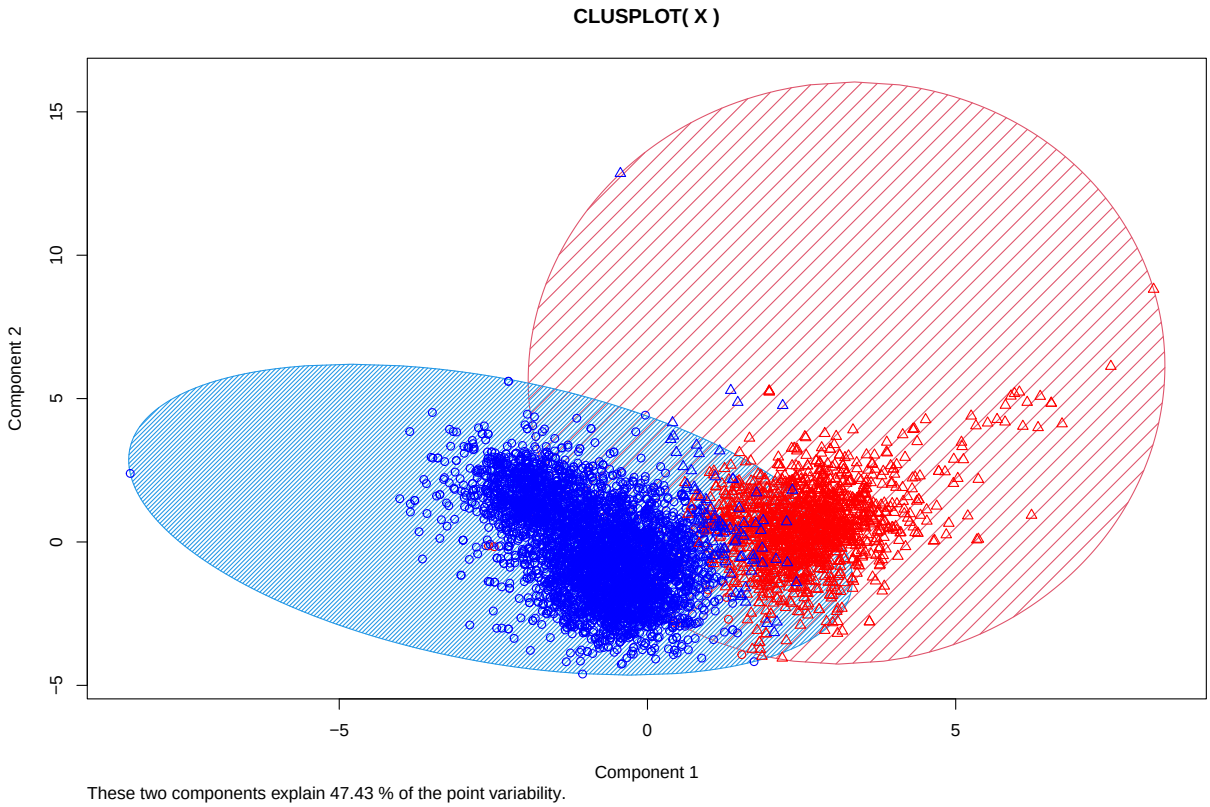
```
##       alcohol     quality
## 1  0.02984993  0.09700235
## 2 -0.08641804 -0.28082994
```

```
library(cluster)
library(fpc)
library(ppclust)
```

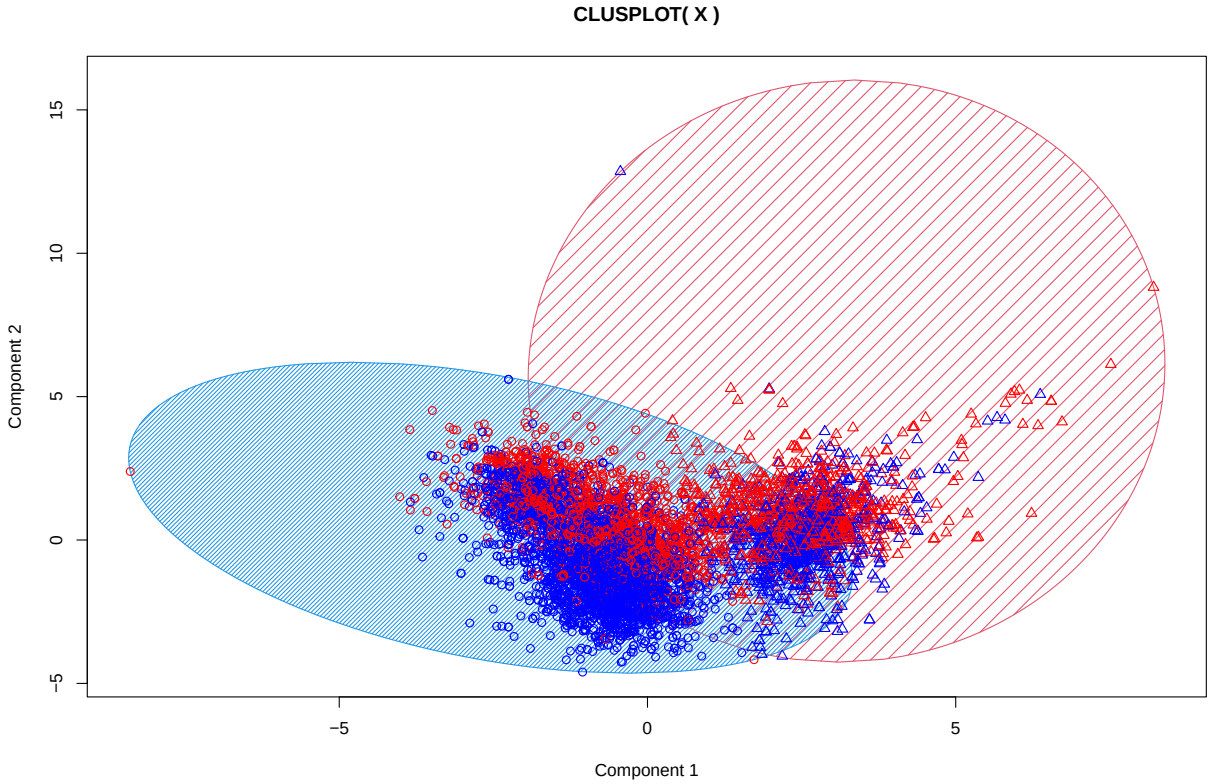
```
##
## Attaching package: 'ppclust'
```

```
## The following object is masked from 'package:fpc':
##
##     plotcluster
```

```
clusplot(X, clust1$cluster, color=TRUE, shade=TRUE,plotchar=TRUE, col.p=wine$color2)
```




```
clusplot(X, clust1$cluster, color=TRUE, shade=TRUE,plotchar=TRUE, col.p=wine$good)
```



Market Segmentation

Data Loading and Processing

```
rm(list=ls())
library(dplyr)
library(RCurl)
```

```
##
## Attaching package: 'RCurl'
```

```
## The following object is masked from 'package:tidyr':
##
##     complete
```

```
df = read.csv("social_marketing.csv")
column_names <-   colnames(df)
column_names[1] <-"user_id"
colnames(df) <-column_names
row.names(df) = df$user_id
rawdf = df %>% select(-c(user_id))
df = rawdf
```

Data Exploration Phase - Let us first take a cursory look at the different tweet categories to figure out what tags are being used in our dataset:

```
c(colnames(df))
```

```
##  [1] "chatter"          "current_events"   "travel"           "photo_sharing"
##  [5] "uncategorized"    "tv_film"          "sports_fandom"    "politics"
##  [9] "food"             "family"           "home_and_garden"  "music"
## [13] "news"             "online_gaming"    "shopping"         "health_nutrition"
## [17] "college_uni"      "sports_playing"   "cooking"          "eco"
## [21] "computers"        "business"         "outdoors"         "crafts"
## [25] "automotive"       "art"              "religion"         "beauty"
## [29] "parenting"        "dating"           "school"           "personal_fitness"
## [33] "fashion"          "small_business"   "spam"             "adult"
```

We know that the variables: **chatter, spam, uncategorized, and adult** are non useful tweets.

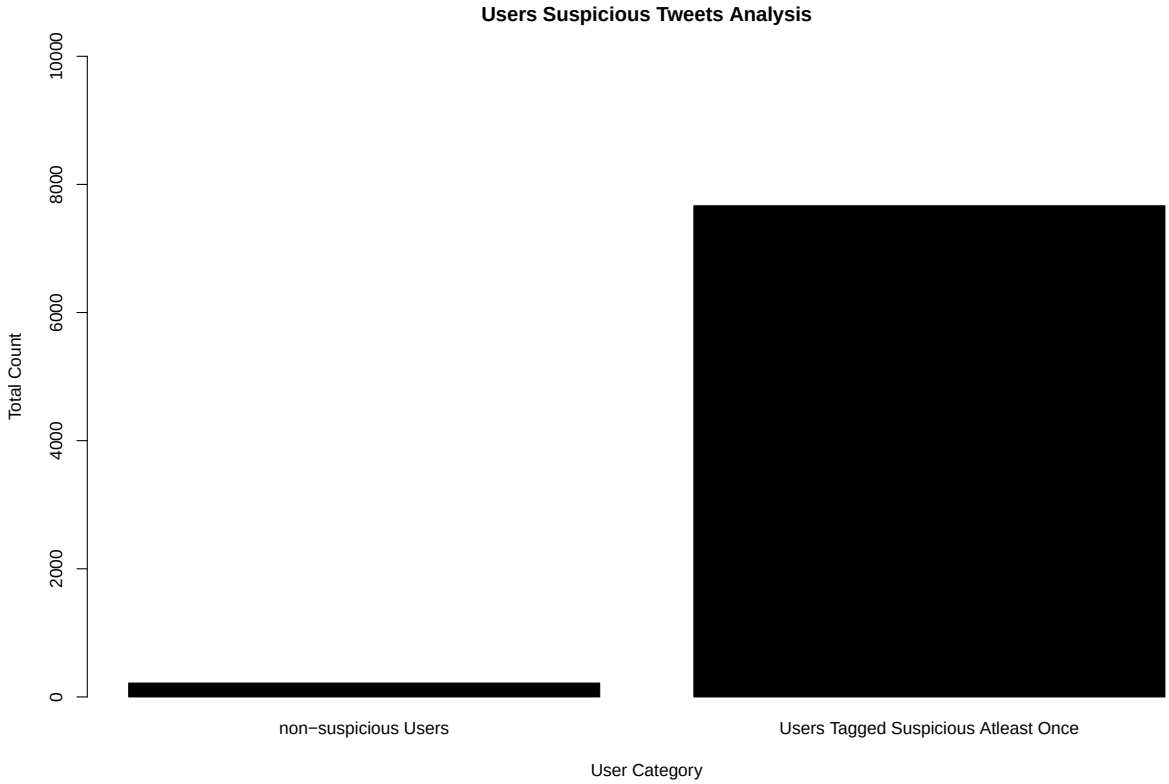
As a first step, we can drop users whose tweets have been tagged under these non useful categories. Let us now check how much data we are left with post this removal.

We will call these categories as **"suspicious categories"**

```
unwanted_cat <- c("spam","chatter","adult","uncategorized")
suspicious_cat_flag = ifelse(rowSums(df %>% select(unwanted_cat))>0,1,0)
```

```
## Note: Using an external vector in selections is ambiguous.
## i Use ‘all_of(unwanted_cat)‘ instead of ‘unwanted_cat‘ to silence this message.
## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This message is displayed once per session.
```

```
df = cbind(df,suspicious_cat_flag)

intdf = df %>% group_by(suspicious_cat_flag) %>% dplyr::summarise(total_records = n())

bp = barplot(intdf$total_records, names.arg = c("non-suspicious Users","Users Tagged Suspicious Atleast
        main = "Users Suspicious Tweets Analysis",
        col= 'Black',
        xlab = 'User Category',
        ylab = 'Total Count',
        ylim = c(0,10000))
```



So, there are only approx **2.7%** users whose tweets have never been categorized under the **suspicious category** as defined by us.

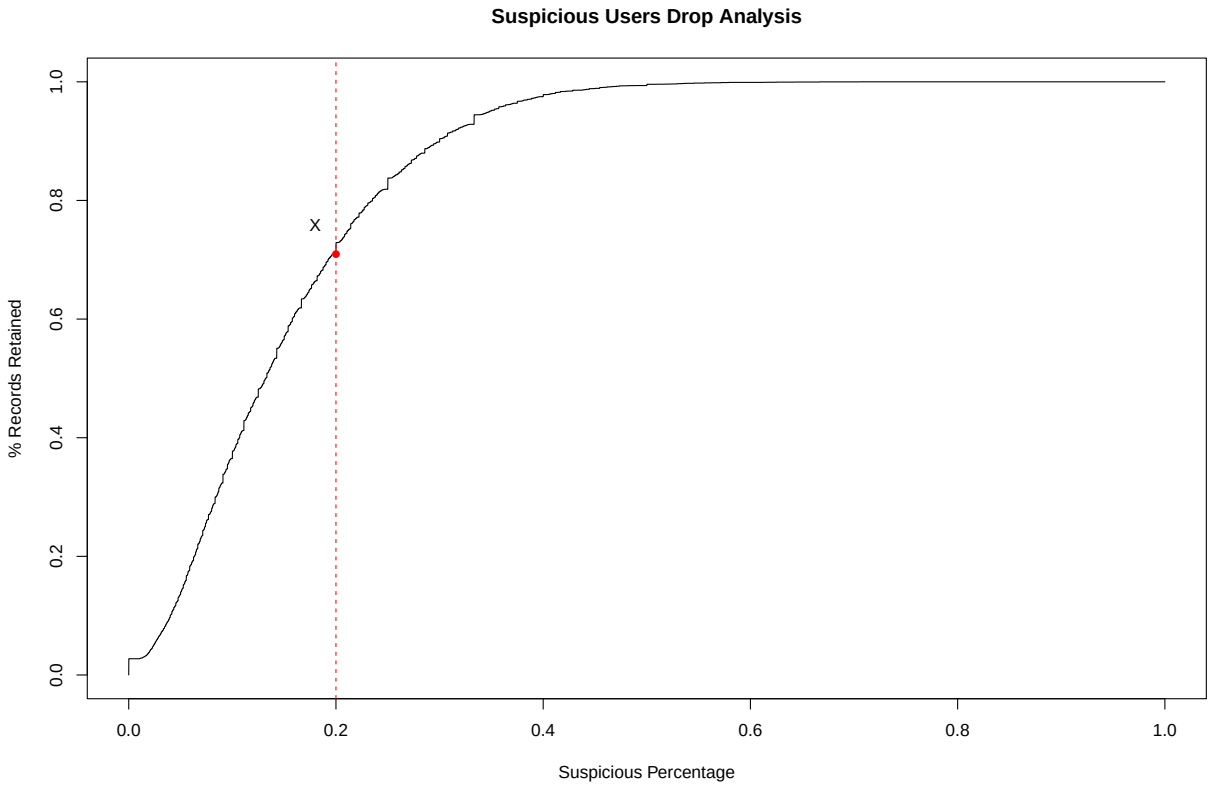
Clearly, we cannot simply delete such a huge number of users (~97%).

We'll define a metric - **suspicious %** as "the no. of Times user's tweet is tagged as suspicious / total tags". This will give the proportion of tweets labeled as suspicious for a particular user.

We can then use this metric to filter out users.

```
## Remove previously created flag
df = df %>% select(- c(suspicious_cat_flag))
suspicious_counts = rowSums(df %>% select(unwanted_cat))
total_counts = rowSums(df)
suspicious_pct = suspicious_counts/total_counts

df = df %>% mutate(suspicious_pct = suspicious_pct)

s1 = seq(0,1,0.0001)
s2 = c()
for (x in s1)
{

  s2 = append(s2, nrow(df %>% filter(suspicious_pct < x))/nrow(rawdf))
}


plot(x = s1,
     y = s2,
```

```
     type = 'l',
     xlab = 'Suspicious Percentage',
     ylab = '% Records Retained',
     main = 'Suspicious Users Drop Analysis'

     )
abline(v = c(0.2), col = 'red',lty = 2)
points(x = 0.2, y = s2[2000], col = 'red', pch = 16)
text(x = 0.18, y = s2[2000]+0.05, "X")
```



We will set the filter threshold at 20%, meaning the users whose suspicious tweets is more than 20% of their total tweets will be filtered out from the dataset.

Threshold is marked by X in above graph. Let us filter the data and remove these unwanted categories

```
analysis_df = df %>% filter(suspicious_pct<0.2) %>% select(- append(unwanted_cat, 'suspicious_pct'))
print(paste0("We are now left with "  ,nrow(analysis_df), " rows"))
```

```
## [1] "We are now left with 5592 rows"
```

Analysis

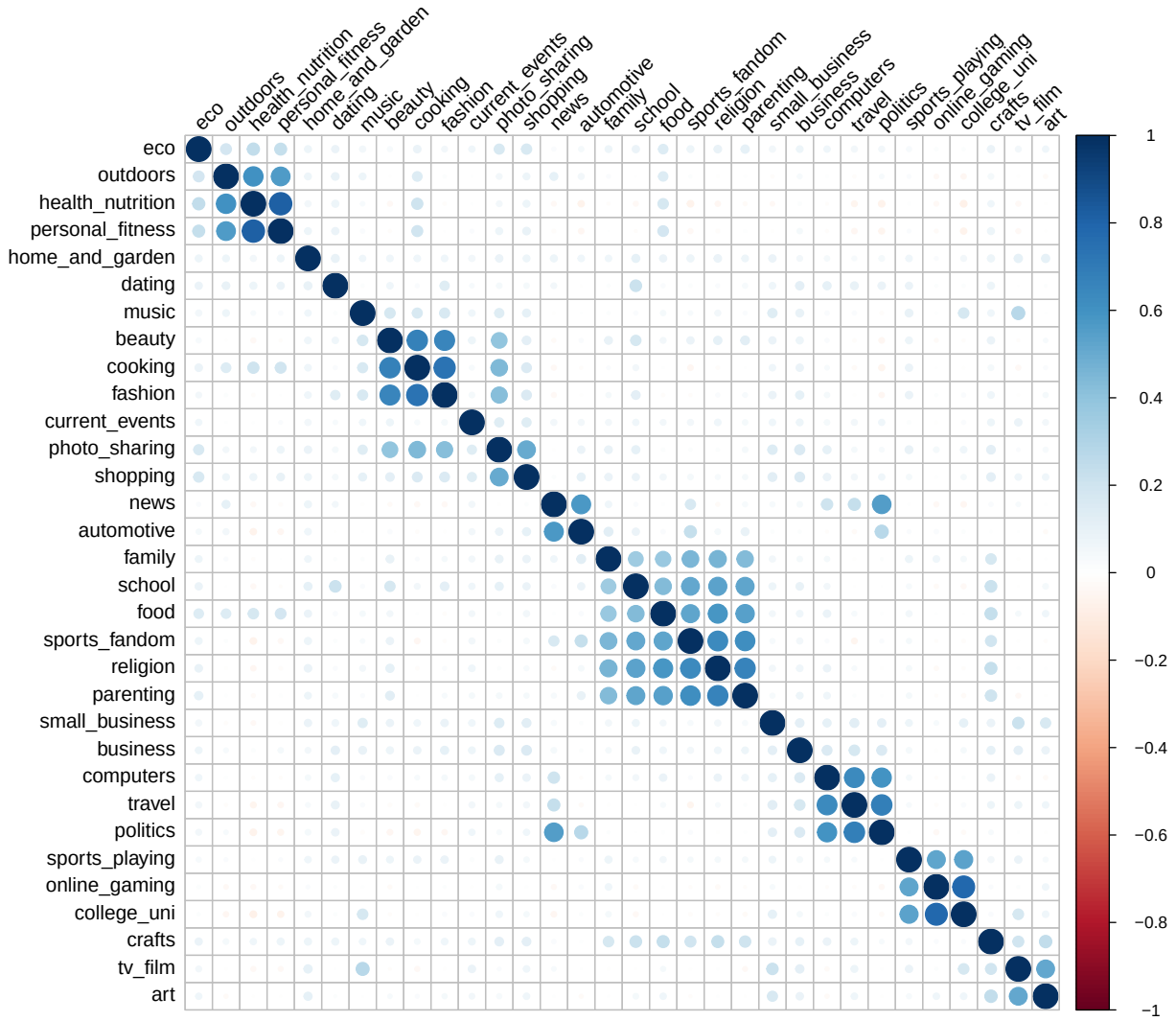
Visualization

Let us try to plot a correlation matrix.

```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
res <- cor(analysis_df)
corrplot(res, order = "hclust", tl.col = "black", tl.srt = 45)
```



Immediately on a cursory glance, we can see 6 clusters in the plot above:

- *Fitness Focused*: Eco, Outdoor, Health_Nutrition, Personal_Fitness
- *Social Media Influencers*: Beauty, Cooking, Fashion

- *Family People* : Family, School, Food, Sports Fandom, Religion, Parenting
- *Geeky traveller*: Computer, Travel, Politics - *Student*: Sports Playing, Online Gaming, College University
- There is a 'not so highly correlated cluster of' art, crafts, and TV film as well

Let us try to reduce the dimensions using Principal Component Analysis

```
Z = scale(analysis_df, center=TRUE, scale=FALSE)
pc_Z = prcomp(Z, rank=10)

summary(pc_Z)
```

```
## Importance of first k=10 (out of 32) components:
##                            PC1    PC2    PC3    PC4     PC5     PC6     PC7
## Standard deviation     5.7539 4.4774 4.3170 4.1992 3.62528 2.44737 2.40030
## Proportion of Variance 0.2217 0.1343 0.1248 0.1181 0.08802 0.04011 0.03858
## Cumulative Proportion  0.2217 0.3560 0.4808 0.5989 0.68688 0.72699 0.76557
##                            PC8     PC9    PC10
## Standard deviation     2.24587 1.79320 1.59931
## Proportion of Variance 0.03378 0.02153 0.01713
## Cumulative Proportion  0.79935 0.82089 0.83801
```

Clearly, we can observe that the proportion of variance explained increases very little after the addition of the 6th component. Thus, we will go ahead with 5 components and analyze them one by one.

```
pc_Z = prcomp(Z, rank=5)
summary(pc_Z)
```

```
## Importance of first k=5 (out of 32) components:
##                            PC1    PC2    PC3    PC4     PC5
## Standard deviation     5.7539 4.4774 4.3170 4.1992 3.62528
## Proportion of Variance 0.2217 0.1343 0.1248 0.1181 0.08802
## Cumulative Proportion  0.2217 0.3560 0.4808 0.5989 0.68688
```

```
# Question 2: how are the individual PCs loaded on the original variables?
loadings = pc_Z$rotation
o1 = order(loadings[,1], decreasing=TRUE)

colnames(Z)[head(o1,10)]
```

```
##  [1] "health_nutrition" "personal_fitness" "cooking"          "outdoors"
##  [5] "photo_sharing"    "fashion"          "food"             "shopping"
##  [9] "beauty"           "eco"
```

```
colnames(Z)[tail(o1,10)]
```

```
##  [1] "computers"     "religion"      "tv_film"       "automotive"
##  [5] "sports_fandom" "news"          "online_gaming" "travel"
##  [9] "college_uni"   "politics"
```

PC1 helps outline health and personal care categories

Let us now analyze PC2

```
# Question 2: how are the individual PCs loaded on the original variables?
loadings = pc_Z$rotation
o1 = order(loadings[,2], decreasing=TRUE)

colnames(Z)[head(o1,10)]
```

```
##  [1] "health_nutrition" "politics"         "personal_fitness" "news"
##  [5] "travel"           "outdoors"         "food"             "computers"
##  [9] "automotive"       "sports_fandom"
```

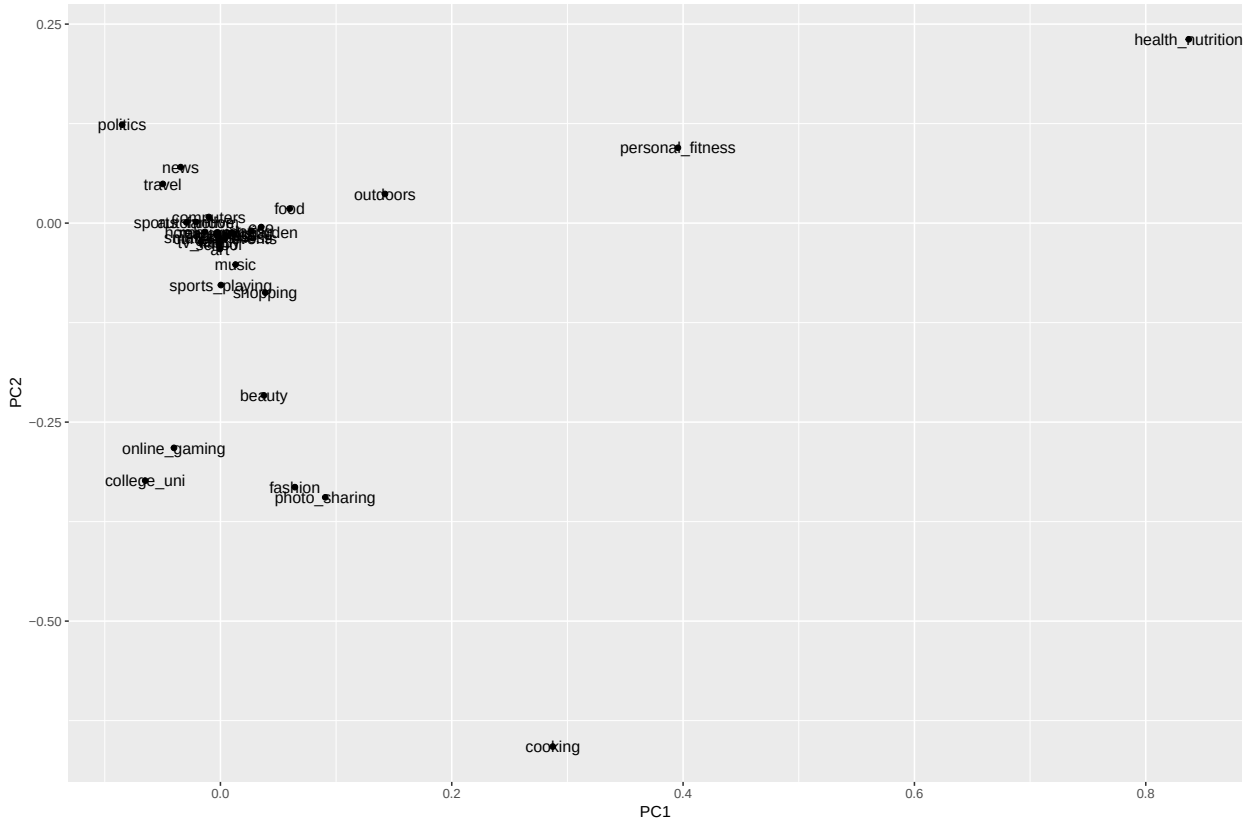
```
colnames(Z)[tail(o1,10)]
```

```
##  [1] "art"            "music"          "sports_playing" "shopping"
##  [5] "beauty"         "online_gaming"  "college_uni"    "fashion"
##  [9] "photo_sharing"  "cooking"
```

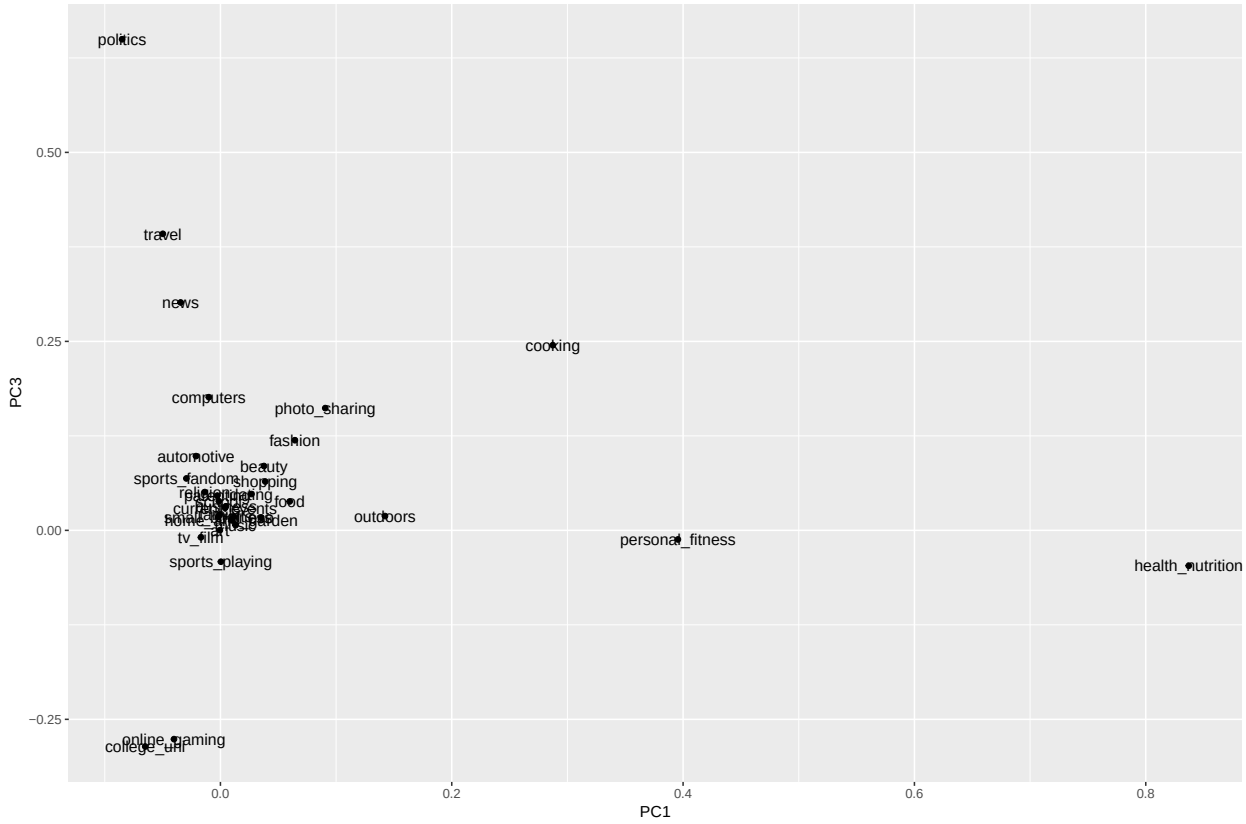
PC2 does not seem to be clearly defined

Let us now try to visualize these Principal Components together in a bi-variate plot

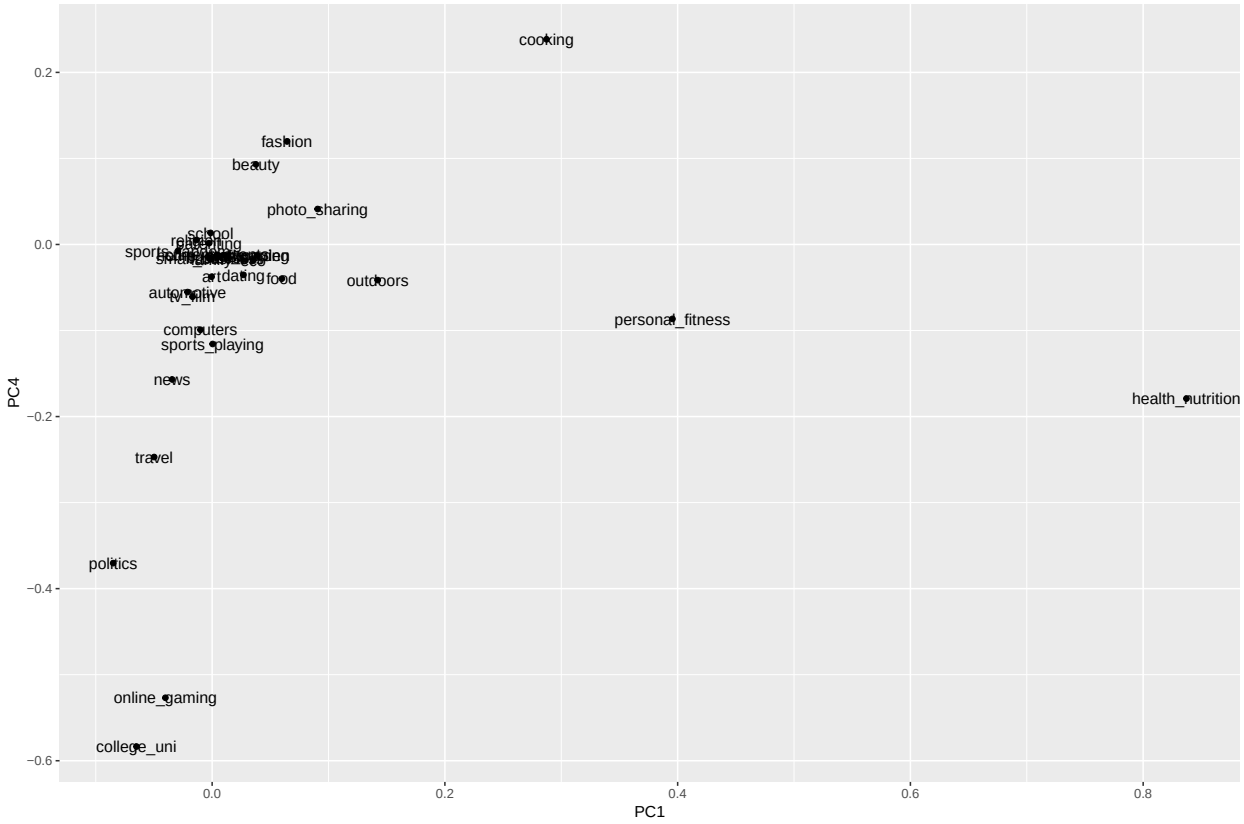
```
library(ggplot2)
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC1, y = PC2))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



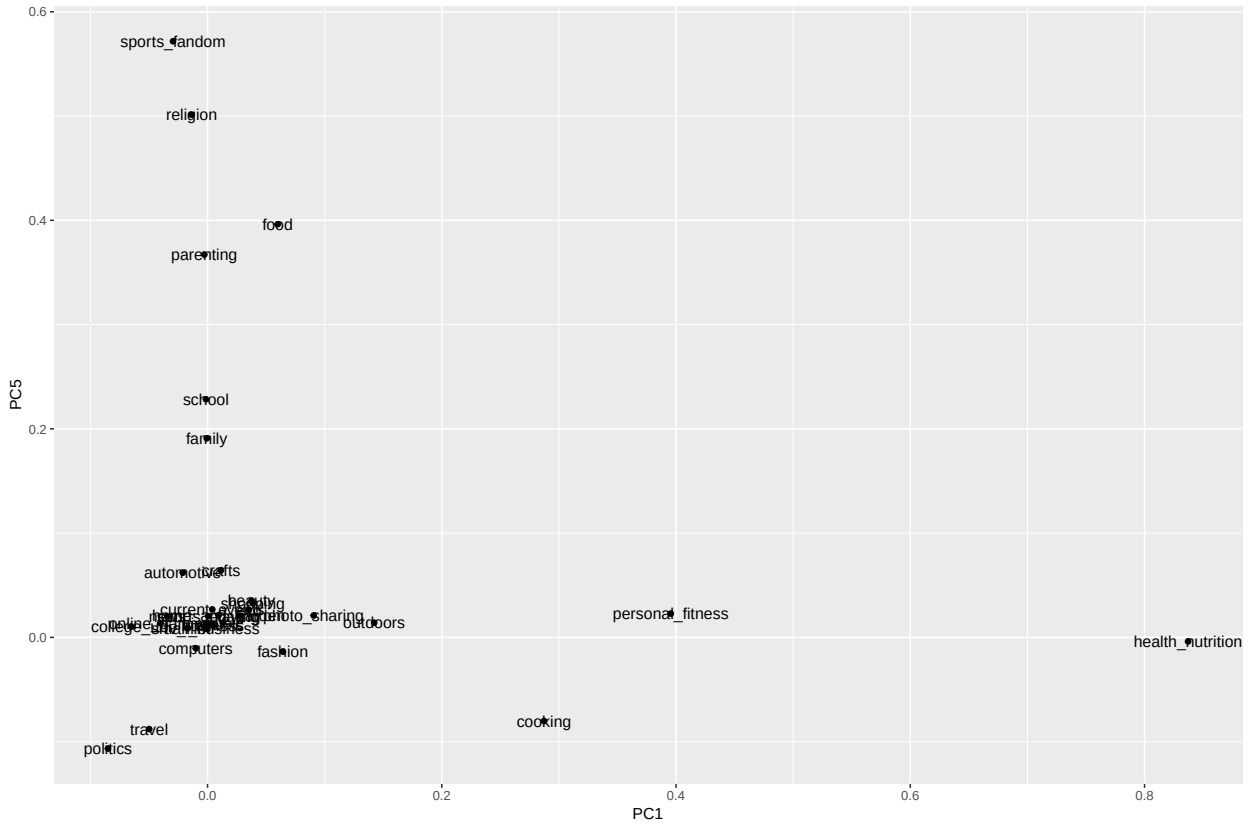

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC1, y = PC3))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



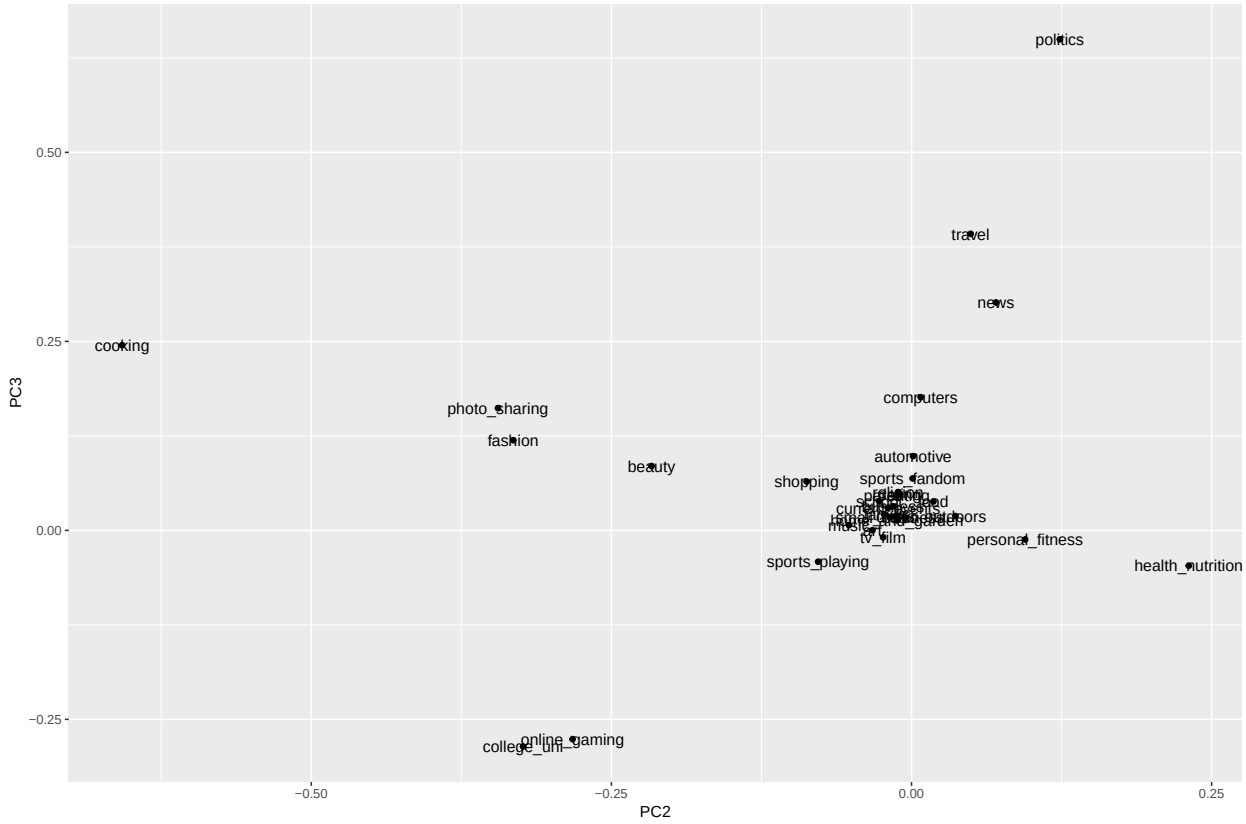

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC1, y = PC4))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



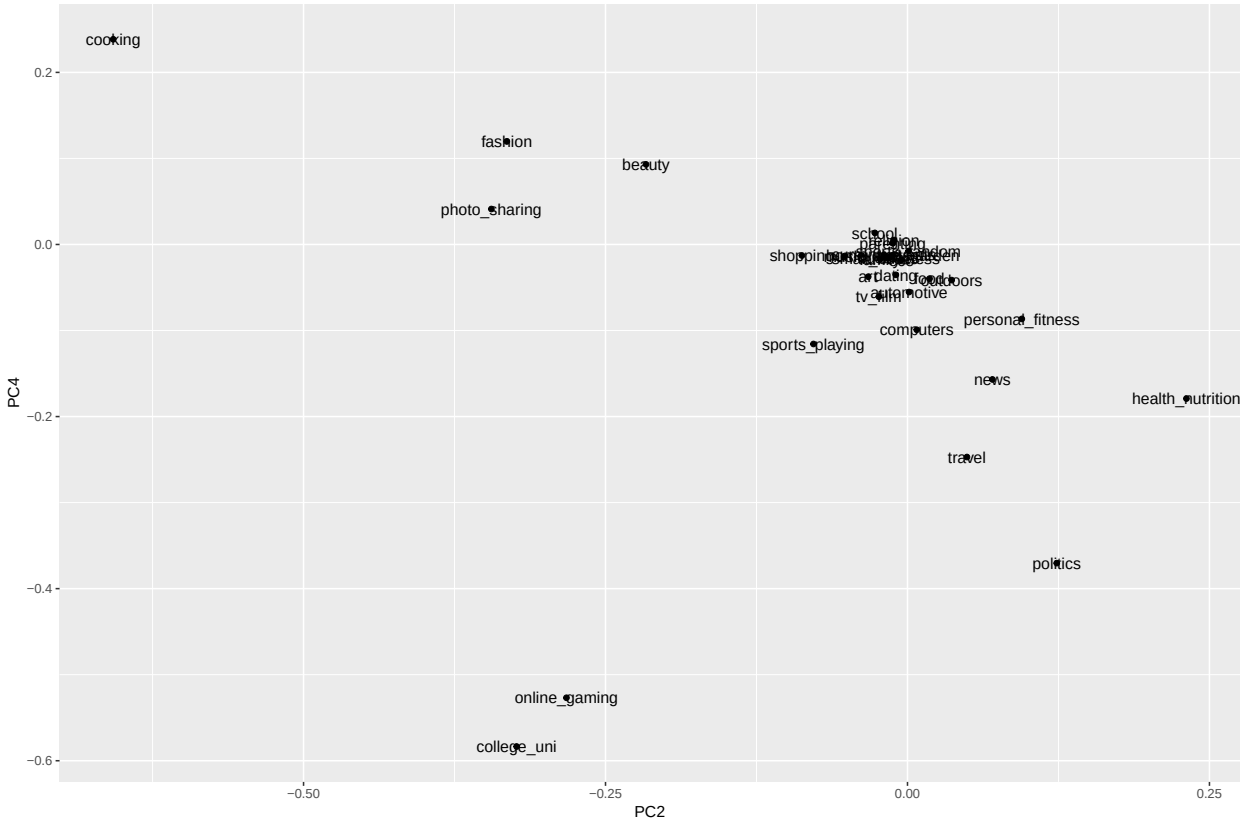

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC1, y = PC5))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



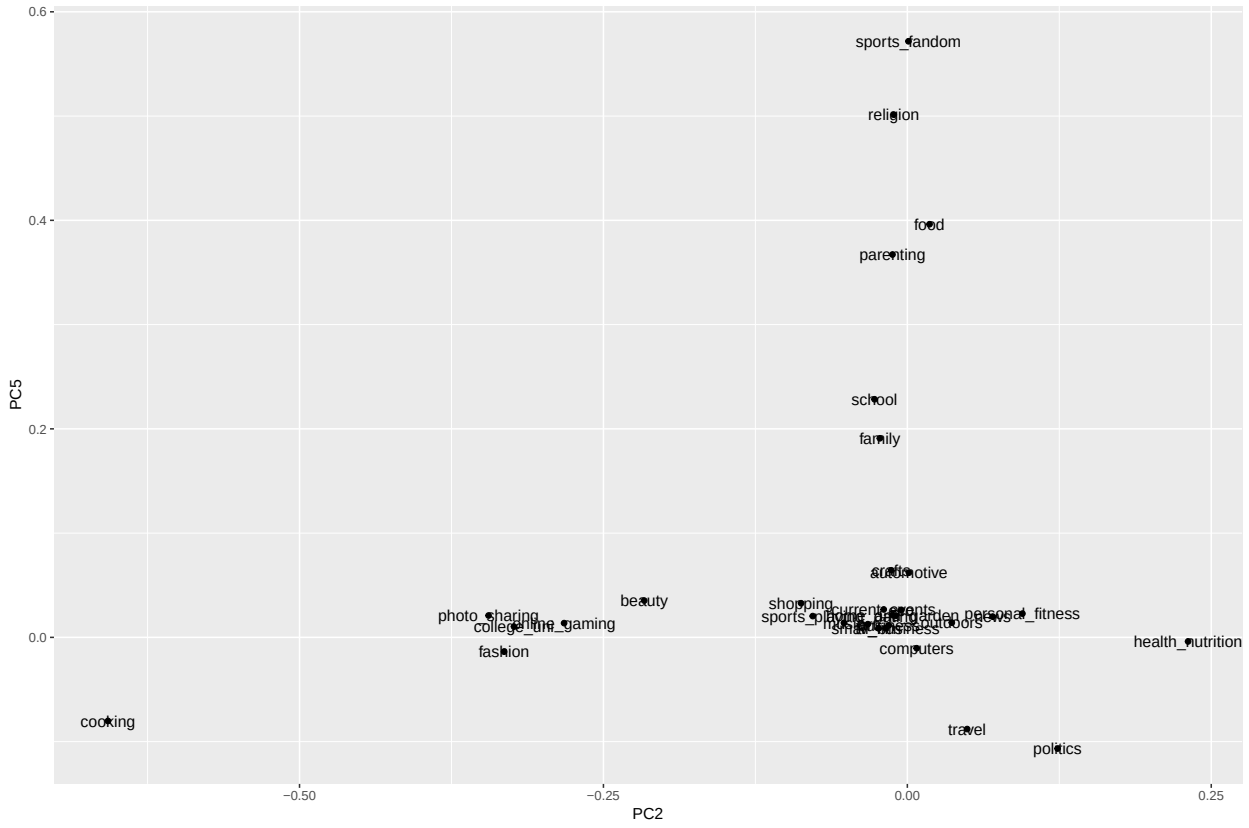

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC2, y = PC3))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



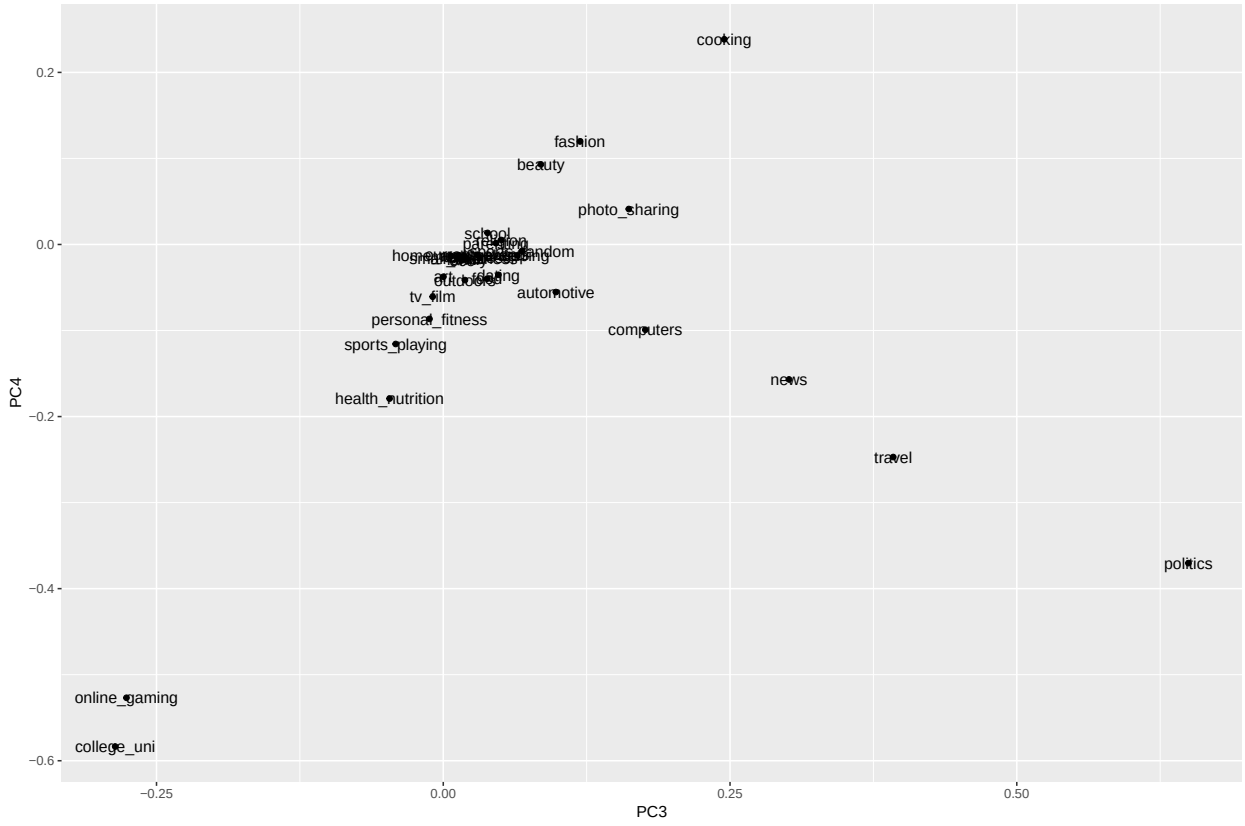

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC2, y = PC4))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



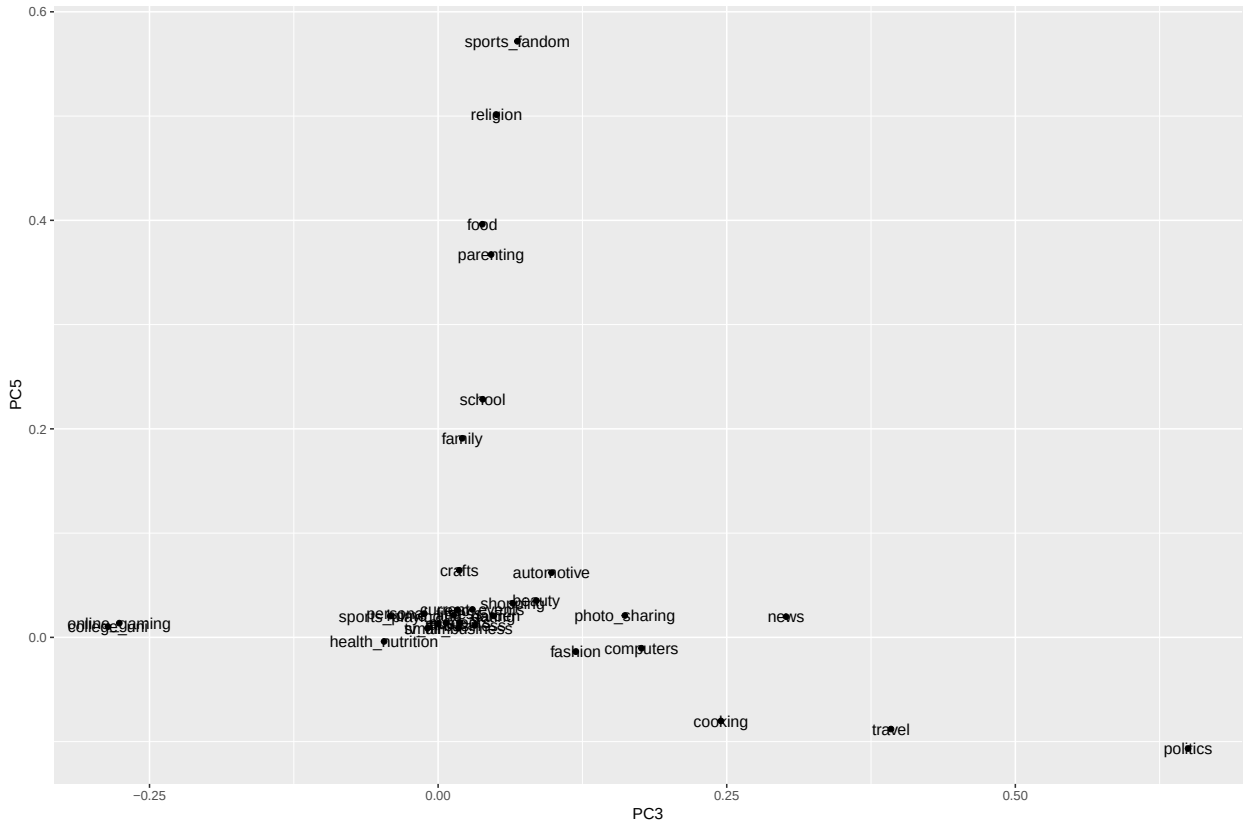

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC2, y = PC5))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



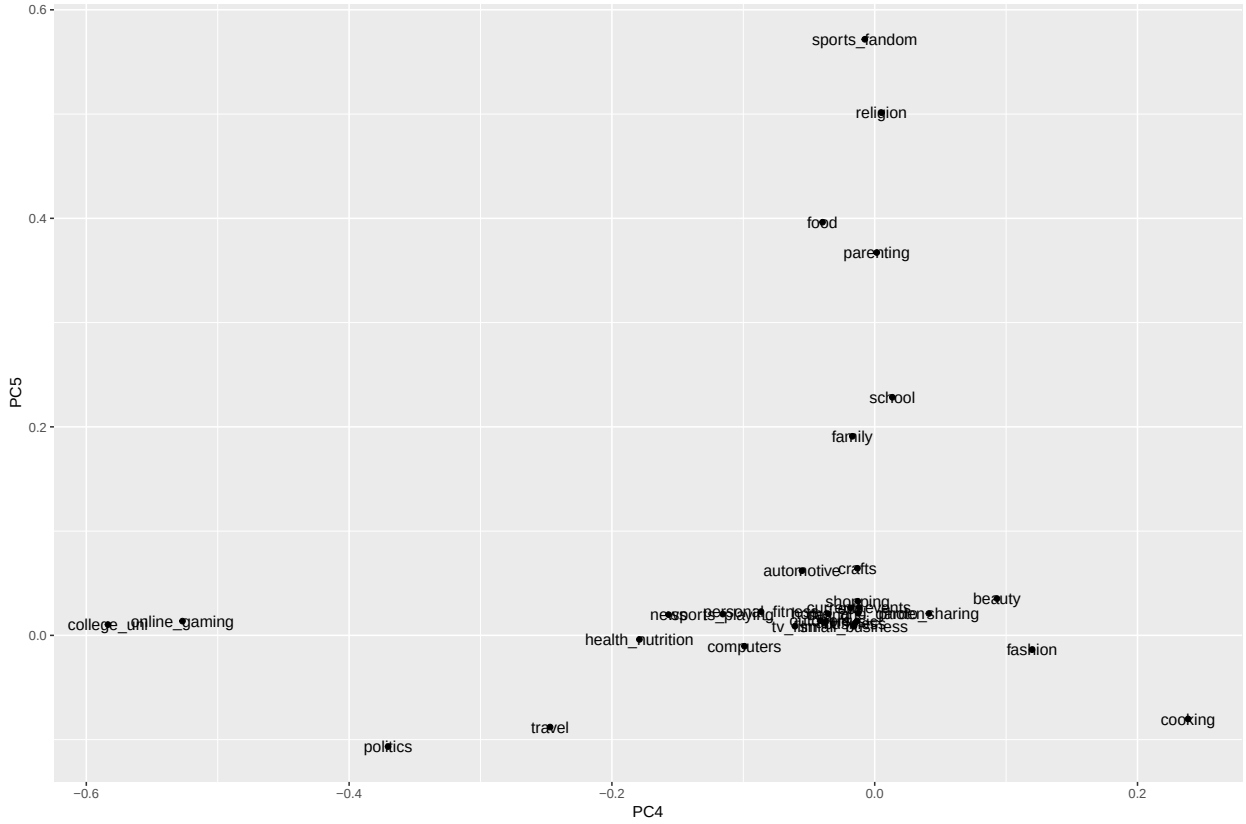

```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC3, y = PC4))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```




```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC3, y = PC5))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```




```
loadings_df <-as.data.frame(loadings)
ggplot(data = loadings_df , aes(x = PC4, y = PC5))+
  geom_point()+
  geom_text(label = rownames(loadings_df))
```



Observations: - PC4 vs PC5 : Separates the family cluster from other clusters; also, to the left is the student cluster

PC4 vs PC2 : Separates the social media influences cluster

A more efficient approach maybe is to cluster these PCs and see which of them are similar

```
library(LICORS)
clust = kmeanspp(loadings_df, k=6) # Add min thresholdz
clust$size
```

```
## [1] 18  3  4  3  2  2
```

```
z = order(clust$cluster)
clust$cluster[z]
```

```
##   current_events          tv_film           family  home_and_garden
##                1                1                1                1
##            music         shopping   sports_playing              eco
##                1                1                1                1
##        computers         business         outdoors           crafts
##                1                1                1                1
##       automotive              art           beauty           dating
##                1                1                1                1
##           school   small_business    photo_sharing          cooking
```

```
##                1                1                2                2
##          fashion    sports_fandom             food         religion
##                2                3                3                3
##        parenting           travel         politics             news
##                3                4                4                4
## health_nutrition personal_fitness    online_gaming      college_uni
##                5                5                6                6
```

```
## No matter how many clusters we try to create, the clusters are very unbalanced indicating that PC ar

# The clusters with less size are clearly distinguishable
```

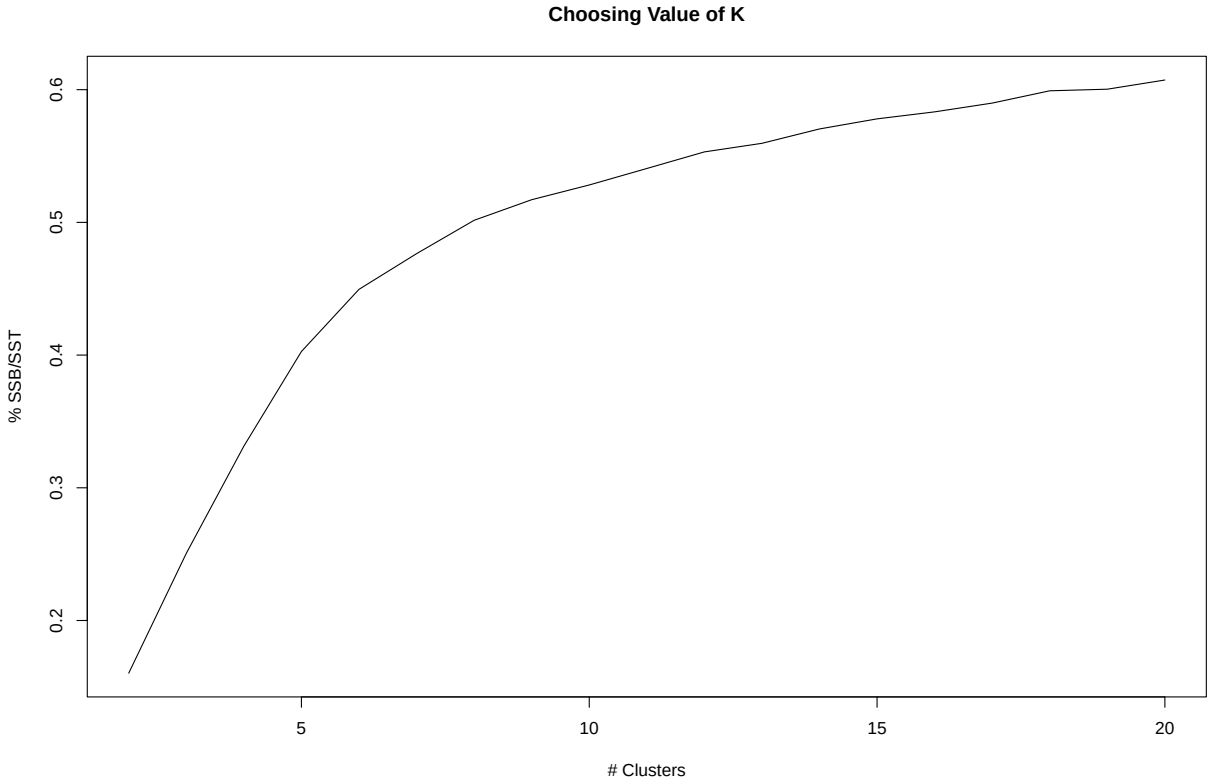
We try to look at all of these PCs to get a concrete sense of what 'trait' do they distinguish but are unable to decipher clearly.

Since this is a a marketing segmentation problem, we will require very good understanding on what the individual PCs are trying to distinguish.

As this clarity is not present, we abandon the idea of PCs completely and try Kmeans++ on the entire data.

K Means for Entire data

```
ratio = c()
clust_counter = c(2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20)
for ( clust_count in clust_counter)
{
clust_total = kmeanspp(Z, k=clust_count)
#clust_df = cbind(Z,clust_total$cluster)
a = clust_total$betweenss/ clust_total$totss
ratio = append(ratio,a)
}

plot(x = clust_counter,
     y = ratio,
     type = 'l',
     xlab = '# Clusters',
     ylab = '% SSB/SST',
     main = 'Choosing Value of K'
     )
```



Along expected lines, optimal number of clusters = 6

Let us fit the final K means model to cluster it

```
clust = kmeanspp(Z, k=6)
### Top category
a = colnames(analysis_df)[max.col(analysis_df, ties.method = "first")]
clust$size
```

```
## [1]  494  618 2675  545  881  379
```

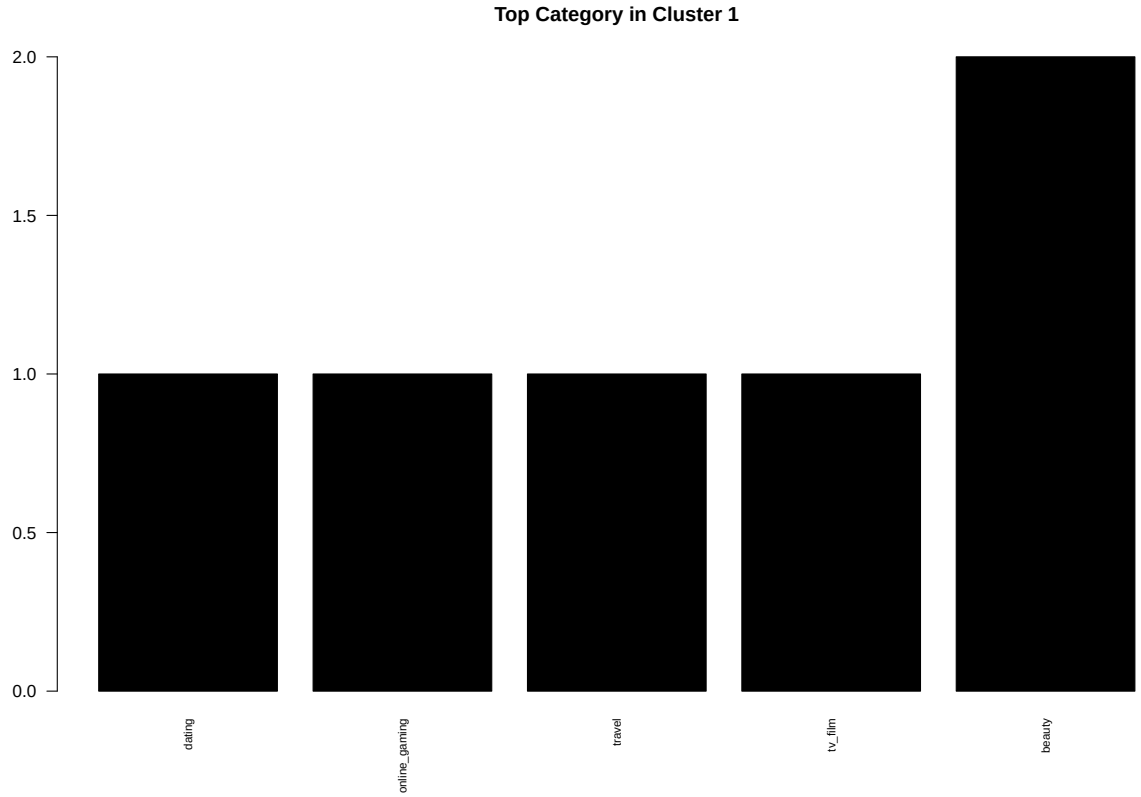
```
### final df post clustering
clustering_df = cbind(analysis_df,clust$cluster, a)

df_1 = clustering_df %>% group_by(`clust$cluster`,a) %>% dplyr::summarise(rcds =n())
```

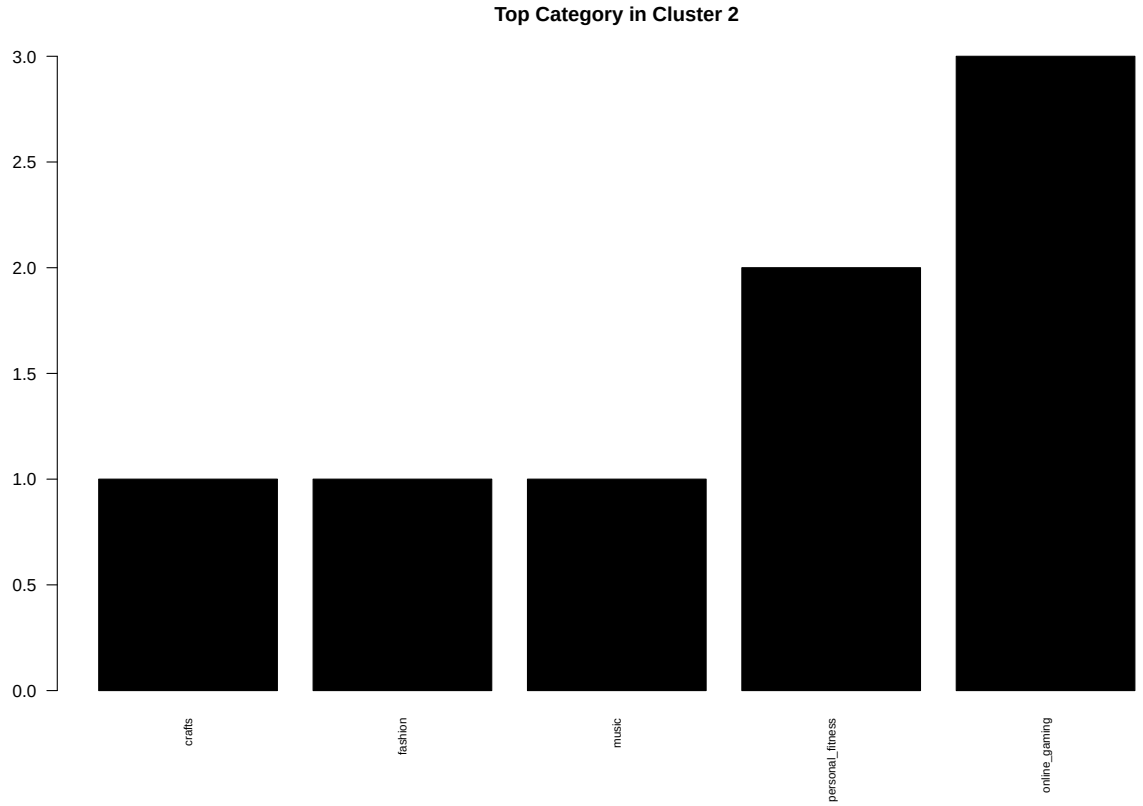
```
## `summarise()` has grouped output by 'clust$cluster'. You can override using the
## `.groups` argument.
```

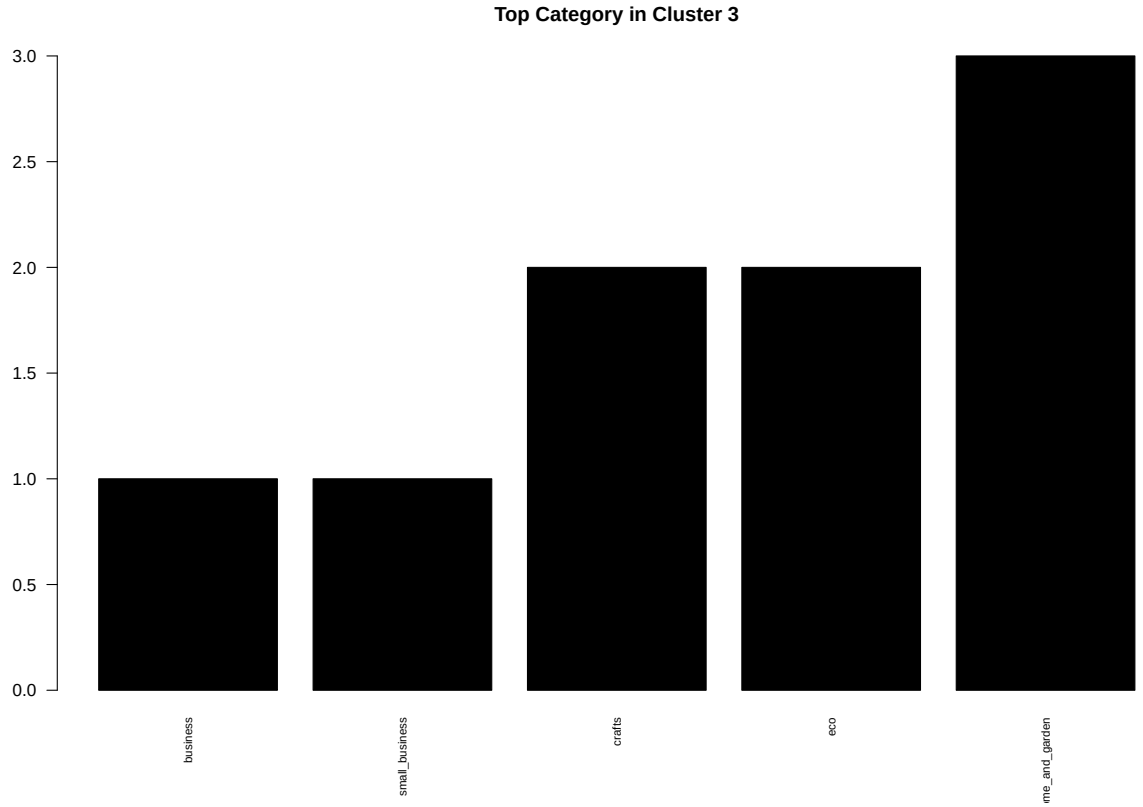
Now let us try to look at the Top 5 most common Tags in Each Cluster

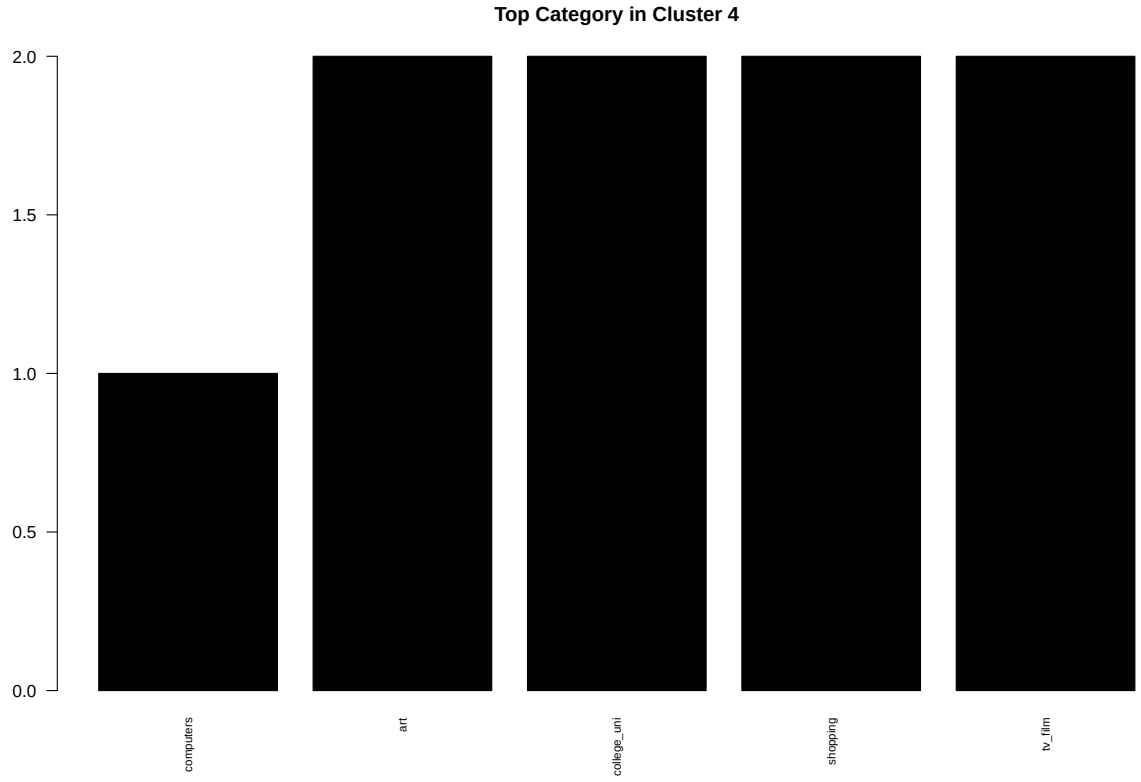
```
top_cat <- df_1 %>%
    dplyr::group_by(`clust$cluster`) %>%
    dplyr::mutate(my_ranks = order(order(rcds, `clust$cluster`))) %>%
    dplyr::filter(my_ranks<=5)
```

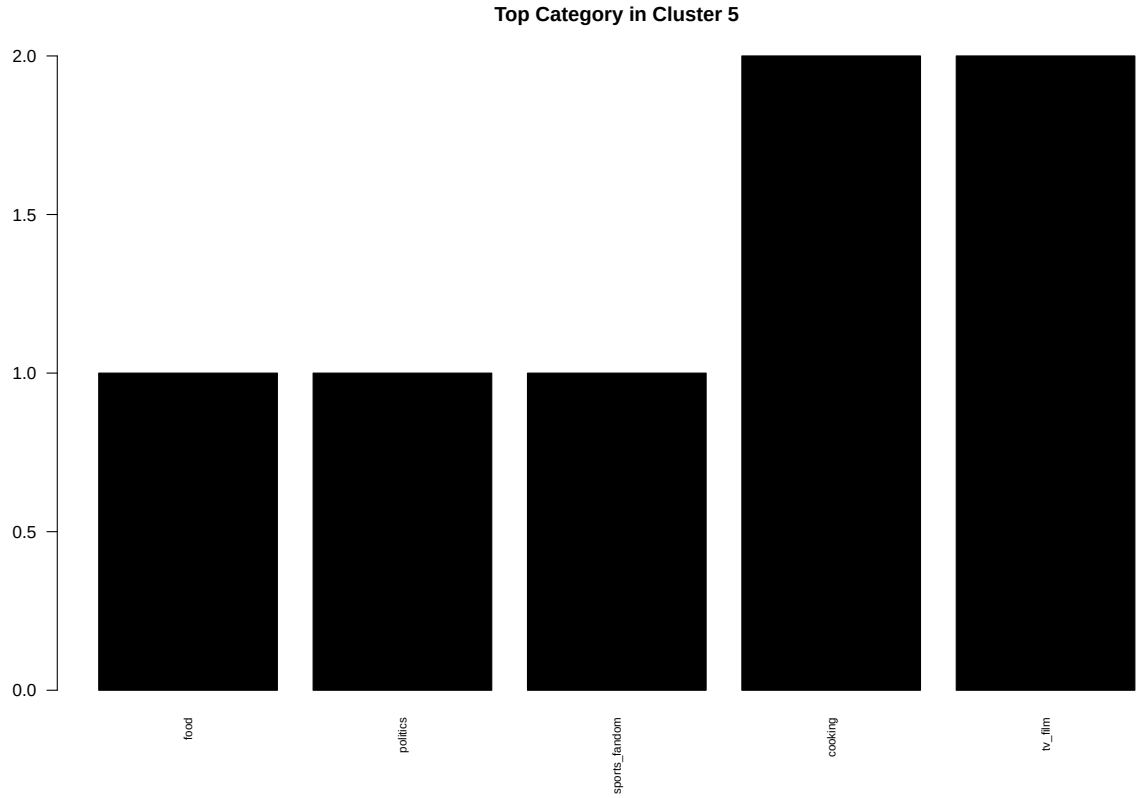
```
for (x in c(1,2,3,4,5,6))
{
  bar_df = top_cat %>% filter(`clust$cluster` == x) %>% dplyr::arrange(rcds)

bp = barplot( bar_df$rcds, names.arg = bar_df$a ,
        main = paste0("Top Category in Cluster ", x),
        col= 'Black', las=2,cex.names=.7)

}
```

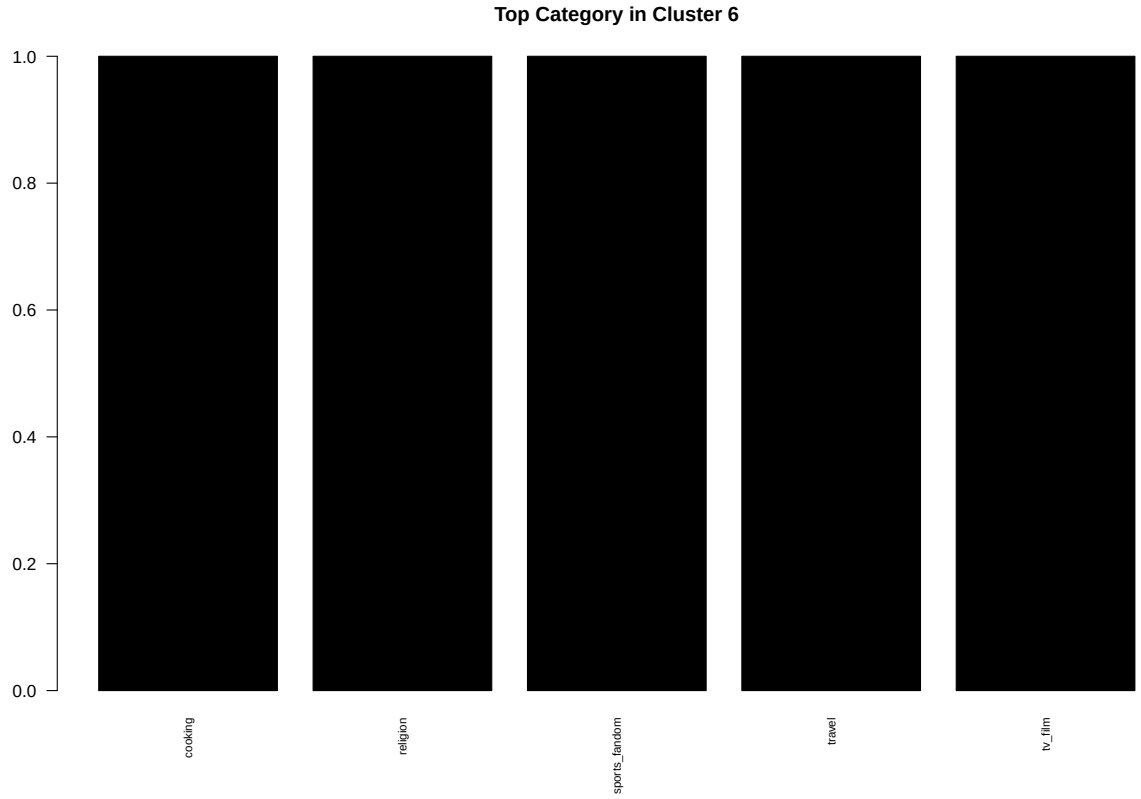



Top Category in Cluster 2
3.0
2.5
2.0
1.5
1.0
0.5
0.0
crafts
fashion
music
personal_fitness
online_gaming


Top Category in Cluster 3
3.0
2.5
2.0
1.5
1.0
0.5
0.0
business
small_business
crafts
eco
me_and_garden


Top Category in Cluster 4
2.0
1.5
1.0
0.5
0.0
computers
art
college_uni
shopping
tv_film


Top Category in Cluster 5
2.0
1.5
1.0
0.5
0.0
food
politics
sports_fandom
cooking
tv_film



So, clearly these **clusters are consistent with what we observed in the correlation plot during our EDA**.

The Reuters Corpus

Step 1. Load files and perform pre-processing steps (for training data)

Step 2. Load files and perform pre-processing steps (for testing data)

Step 3. Peform PCA for Dimensionality reduction ** We will plot a variance plot::

We can select till PC800 as almost 80% of variance explained by them

Step 4. Build Random Forest models to identify authors The model built using Random forest predicted 1844 documents correctly with its respetive authors and gave us accuracy of ~74%.

Association rule mining

Aim

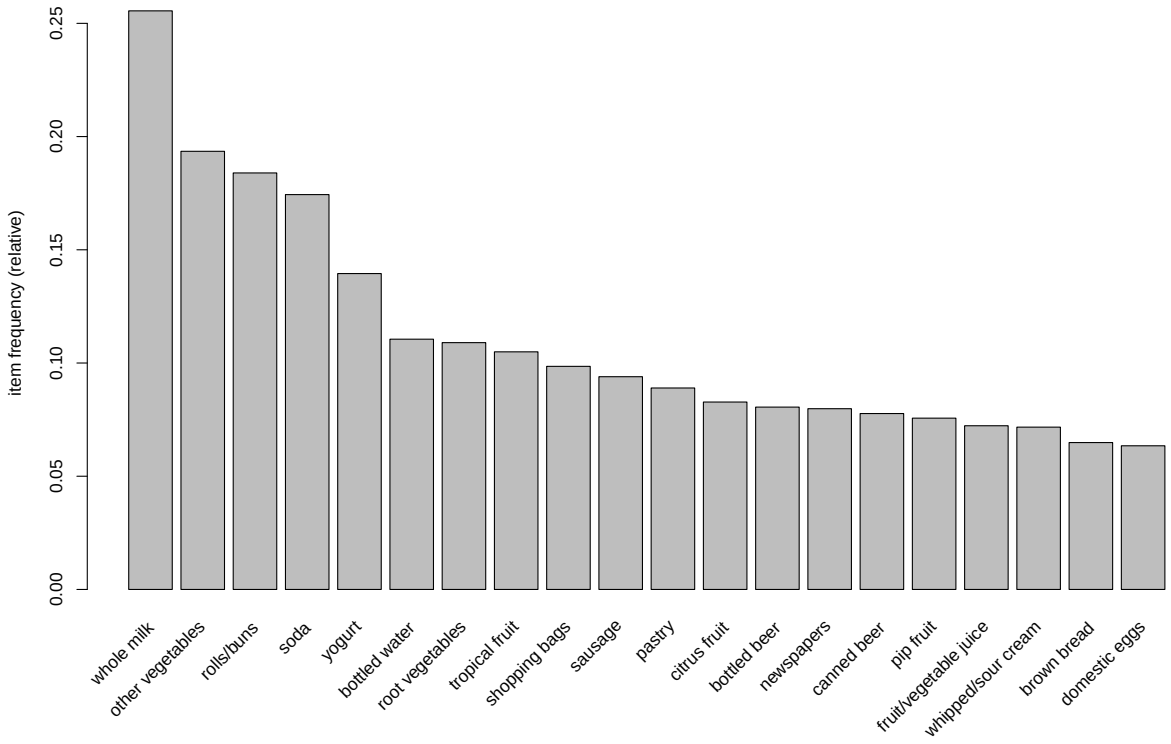
We have multiple shopping baskets of grocery purchases and we will find some interesting association rules between then using rule mining.

Let's see the raw dataset:

```
## [1] "citrus fruit,semi-finished bread,margarine,ready soups"
## [2] "tropical fruit,yogurt,coffee"
## [3] "whole milk"
## [4] "pip fruit,yogurt,cream cheese ,meat spreads"
## [5] "other vegetables,whole milk,condensed milk,long life bakery product"
## [6] "whole milk,butter,yogurt,rice,abrasive cleaner"
```

The apriori algorithm needs the data to be transformed into "transactions" class before we can use the raw data:

Let's plot the transformed dataset to look at the frequency



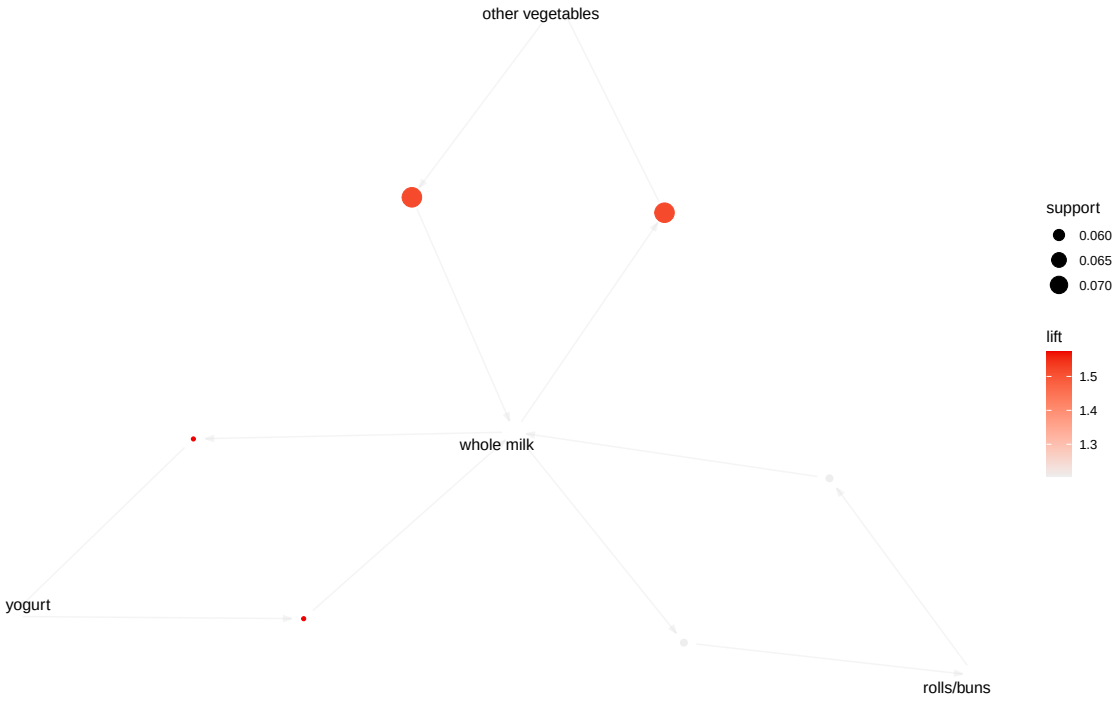
Here is a summary of the dataset:

1. Total of 9835 transactions in the dataset
2. Most of the transactions have 4 or lesser amount of items in the basket
3. The most frequently bought item is whole milk which was present in 2513 transactions

Let's try out the 'apriori' algo with support > 0.05, confidence > 0.1 and length <= 2

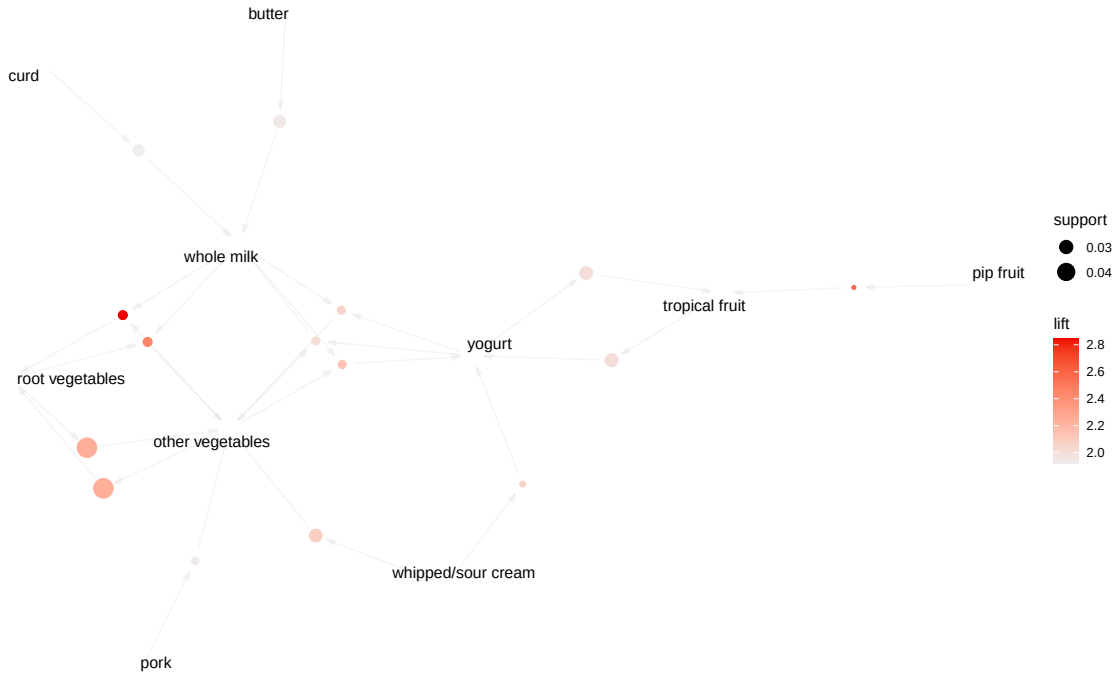
There are only 6 rules generated because of the high support and low confidence level. We also notice that most relationships in this item set include whole milk, yogurt and rolls/buns which is in accordance with the transaction frequency plot we saw earlier. These are some of the most frequently bought items.

```
##     lhs                   rhs                support    confidence coverage
## [1] {yogurt}           => {whole milk}       0.05602440 0.4016035  0.1395018
## [2] {whole milk}       => {yogurt}           0.05602440 0.2192598  0.2555160
## [3] {rolls/buns}       => {whole milk}       0.05663447 0.3079049  0.1839349
## [4] {whole milk}       => {rolls/buns}       0.05663447 0.2216474  0.2555160
## [5] {other vegetables} => {whole milk}       0.07483477 0.3867578  0.1934926
## [6] {whole milk}       => {other vegetables} 0.07483477 0.2928770  0.2555160
##     lift     count
## [1] 1.571735 551
## [2] 1.571735 551
## [3] 1.205032 557
## [4] 1.205032 557
## [5] 1.513634 736
## [6] 1.513634 736
```



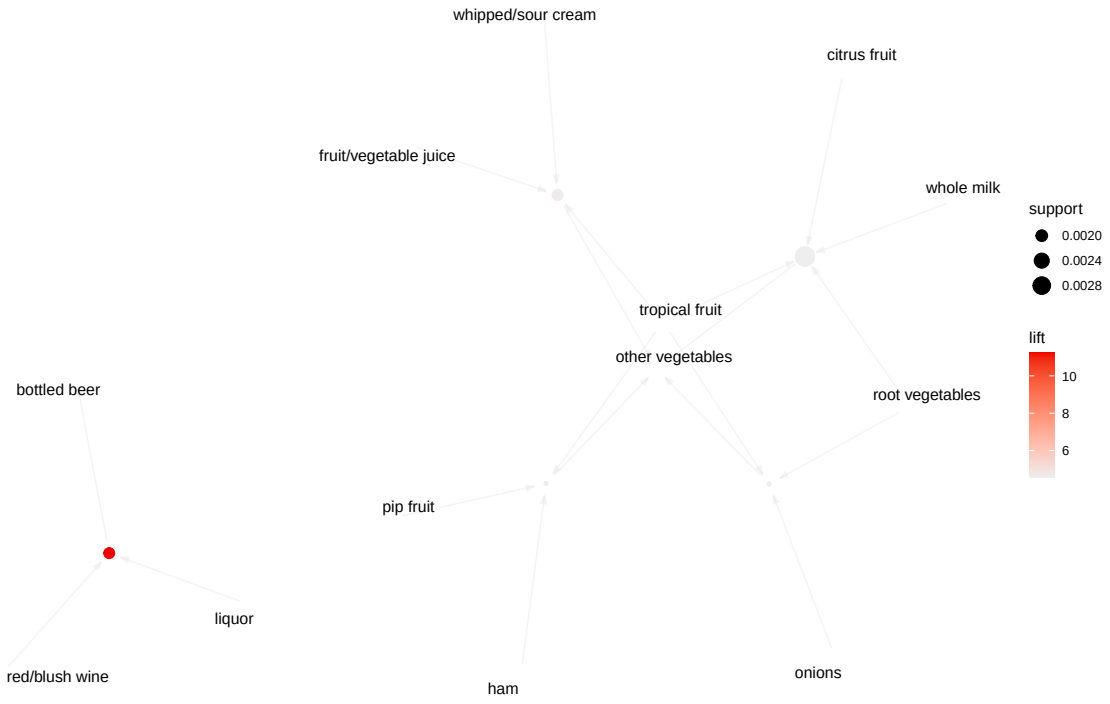
Let's try decreasing the support and increase confidence slightly with support > 0.02, confidence > 0.2 and length <= 2

Now we get 72 rules with a lot more items. Again we can notice that whole milk is a common occurance.



**** Let's try increasing the confidence level and decrease the support further. Let's explore rules with support > 0.0015, confidence > 0.8 and length <=2**

This time we get 60 rules and again can notice that whole milk is the most frequent item as expected



Summary

From the association rules, some of the conclusions that can be drawn are:

1. People are more likely to buy bottled beer if they purchased red wine or liquor
2. People are more likely to buy vegetables when they buy vegetable/fruit juice
3. Whole milk is the most common item purchased by customers