Assignment1_WenyueShi

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Set a global seed

```r
set.seed(1984)
```

Exploratory analysis

Load the mosaic library and import the data

```r
library(mosaic)

## Loading required package: car
## Loading required package: dplyr
##
## Attaching package: 'dplyr'
##
## The following objects are masked from 'package:stats':
##
##     filter, lag
##
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
##
## Loading required package: lattice
## Loading required package: ggplot2
## Loading required package: mosaicData
##
## Attaching package: 'mosaic'
##
## The following objects are masked from 'package:dplyr':
##
##     count, do, tally
##
## The following object is masked from 'package:car':
##
##     logit
##
## The following objects are masked from 'package:stats':
##
##     binom.test, cor, cov, D, fivenum, IQR, median, prop.test,
##     quantile, sd, t.test, var
##
```

```
## The following objects are masked from 'package:base':
##
##     max, mean, min, prod, range, sample, sum
```

```
vote = read.csv('../data/georgia2000.csv')
```

Take a look at the data frame by looking at the summary.

```
summary(vote)
```

```
##       county       ballots            votes              equip
##  APPLING :  1   Min.   :   881   Min.   :   832   LEVER   :74
##  ATKINSON:  1   1st Qu.:  3694   1st Qu.:  3506   OPTICAL:66
##  BACON   :  1   Median :  6712   Median :  6299   PAPER   : 2
##  BAKER   :  1   Mean   : 16926   Mean   : 16331   PUNCH   :17
##  BALDWIN :  1   3rd Qu.: 12251   3rd Qu.: 11846
##  BANKS   :  1   Max.   :280975   Max.   :263211
##  (Other) :153
##       poor             urban            atlanta             perAA
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.00000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0.1115
##  Median :0.0000   Median :0.0000   Median :0.00000   Median :0.2330
##  Mean   :0.4528   Mean   :0.2642   Mean   :0.09434   Mean   :0.2430
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0.3480
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.00000   Max.   :0.7650
##
##       gore              bush
##  Min.   :   249   Min.   :   271
##  1st Qu.:  1386   1st Qu.:  1804
##  Median :  2326   Median :  3597
##  Mean   :  7020   Mean   :  8929
##  3rd Qu.:  4430   3rd Qu.:  7468
##  Max.   :154509   Max.   :140494
##
```

Calculate the undercount_percentage

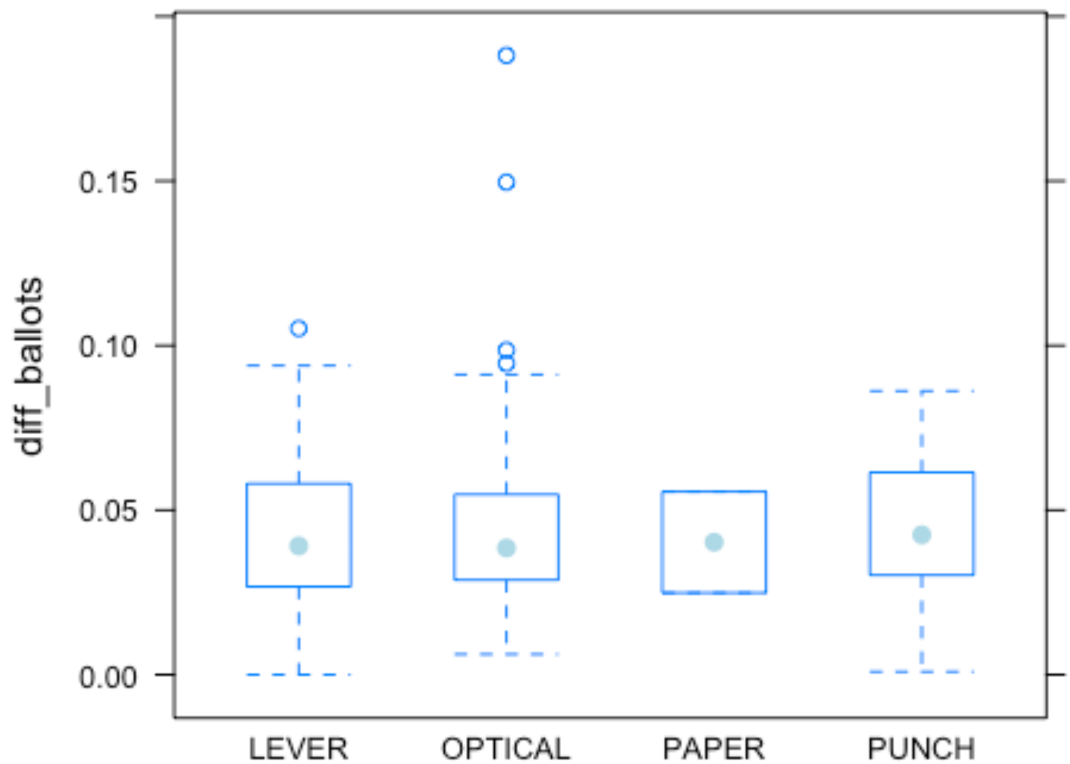
$$(\text{ballots} - \text{votes})/\text{ballots}$$

and add the percentage to the original data set.

```
diff = vote$ballots - vote$votes
vote$diff <- diff
diff_ballots = vote$diff/vote$ballots
vote$diff_ballots = diff_ballots
```

Boxplot the percentage:

```
bwplot(diff_ballots~equip, data = vote, col = "Light Blue", outline =
FALSE)
```



From the boxplot, in general, different equipment of voting does not lead to higher rate of undercount.

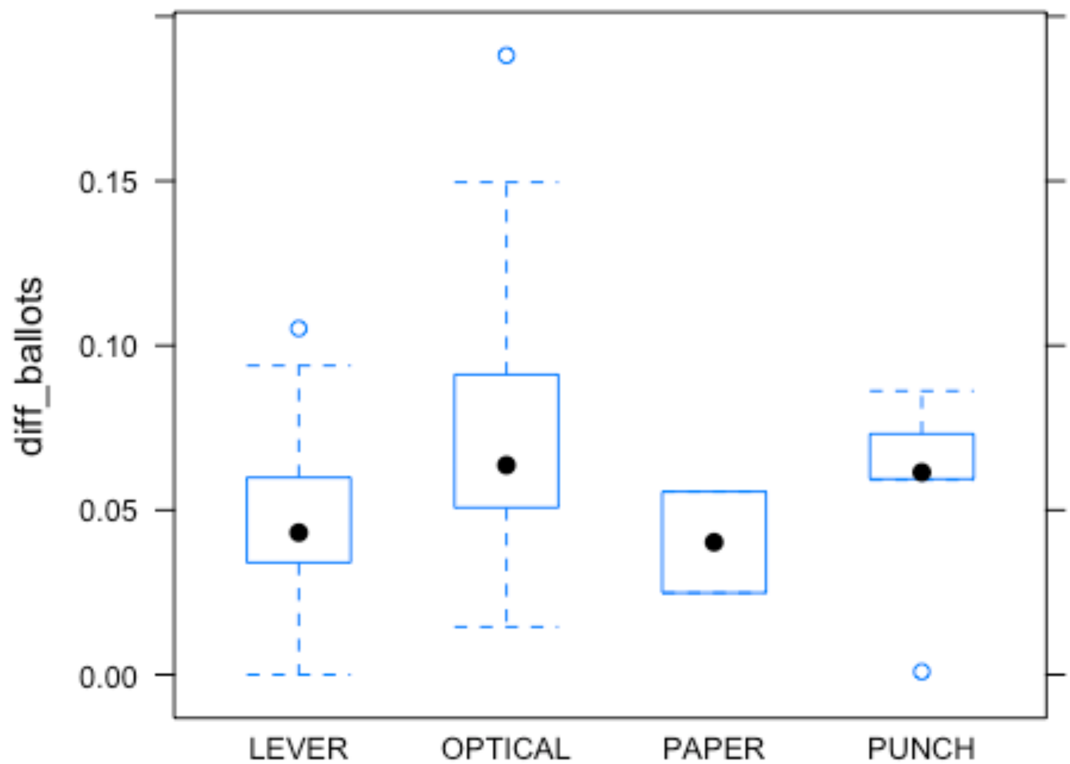
Poor Areas

But then we want to see whether different equipment does affect undercount in poor area. Select the poor observation out, where

$$\text{poor} = 1$$

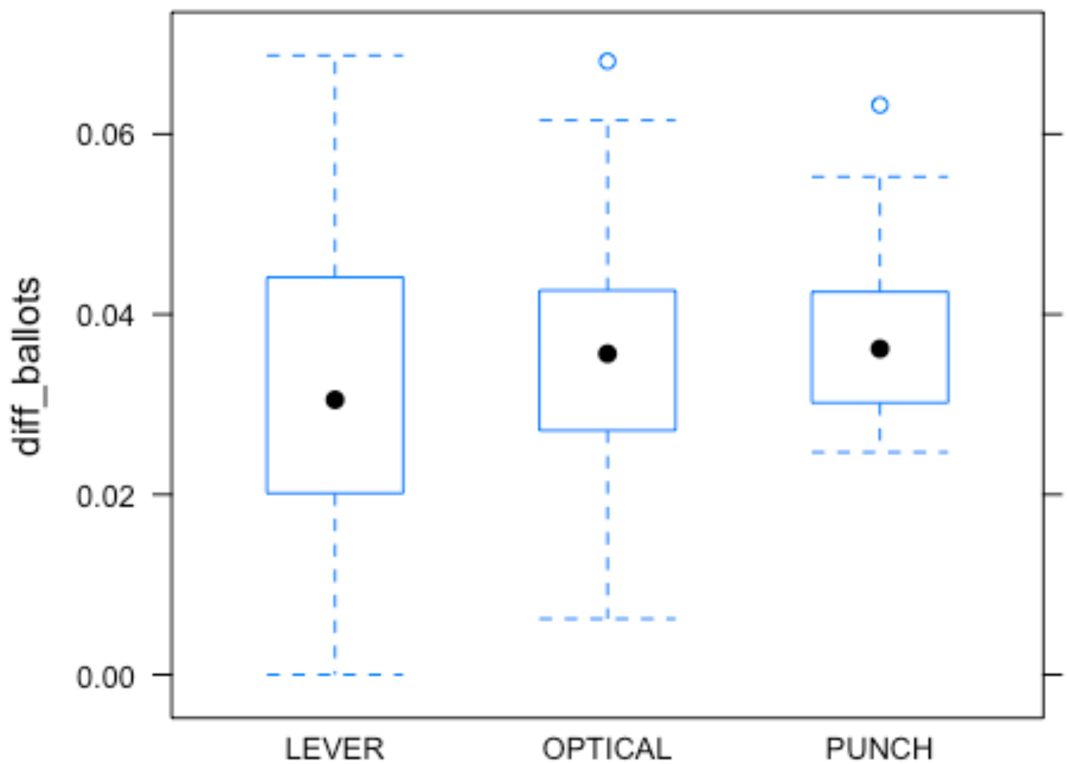
and plot the undercount percentage again with the boxplot.

```
poor <- vote[vote$poor == 1, ]
bwplot(diff_ballots~equip, data = poor)
```



Obviously, optical and punch lead to a higher level of undercount than lever and paper. To compare with non-poor areas, I did the similar thing to non-poor area.

```
notpoor <- vote[vote$poor == 0, ]
bwplot(diff_ballots~equip, data = notpoor)
```



Clearly, equipment doesn't obviously affect the undercount level, even though optical and punch still generate a little bit higher undercount.

Overall, poor areas have

- higher undercount_percentage than non-poor areas
- remarkable different undercount value with different equipments

Minority Areas

Now let's take a look at minority communities. Since perAA (the percentage of African American) is a quantatative feature, we'd like to run four linear regression between undercount percentaeg level and perAA under the situation of different equipments.

```
lever = vote[vote$equip == 'LEVER', ]
optical = vote[vote$equip == 'OPTICAL', ]
paper = vote[vote$equip == 'PAPER', ]
punch = vote[vote$equip == 'PUNCH', ]

lm.lever = lm(diff_ballots~perAA, data = lever)
summary(lm.lever)
```

```
##
## Call:
## lm(formula = diff_ballots ~ perAA, data = lever)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.042857 -0.014572 -0.003374  0.015299  0.062319
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.043712   0.004783   9.139 1.15e-13 ***
## perAA       -0.006584   0.014897  -0.442     0.66
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02097 on 72 degrees of freedom
## Multiple R-squared:  0.002706,   Adjusted R-squared:  -0.01115
## F-statistic: 0.1954 on 1 and 72 DF,  p-value: 0.6598
```

```
lm.optical = lm(diff_ballots~perAA, data = optical)
summary(lm.optical)
```

```
##
## Call:
## lm(formula = diff_ballots ~ perAA, data = optical)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.037657 -0.012688 -0.002691  0.008405  0.132622
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.025166   0.005342   4.711 1.37e-05 ***
## perAA       0.107561   0.022993   4.678 1.55e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02599 on 64 degrees of freedom
## Multiple R-squared:  0.2548, Adjusted R-squared:  0.2432
## F-statistic: 21.88 on 1 and 64 DF,  p-value: 1.546e-05
```

```
lm.punch = lm(diff_ballots~perAA, data = punch)
summary(lm.punch)
```

```
##
## Call:
## lm(formula = diff_ballots ~ perAA, data = punch)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.048304 -0.007817  0.004888  0.013611  0.026992
```

```
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.03063    0.01014   3.021  0.00859 **
## perAA        0.05517    0.02967   1.859  0.08269 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02035 on 15 degrees of freedom
## Multiple R-squared:  0.1873, Adjusted R-squared:  0.1331
## F-statistic: 3.458 on 1 and 15 DF,  p-value: 0.08269
```

For Lever equipment, perAA seems don't have a correlation with undercounts. But for optical method and punch method, the coefficients of perAA are $1.55 * 10^(- 5)$ and 0.0826 perspectively, indicating that the more African American, the more likely to have undercount with Optical and Punch equipment.

BootStraping:

Library related packages:

```
library(mosaic)
library(fImport)

## Loading required package: timeDate
## Loading required package: timeSeries

library(foreach)
```

Import the five year price from 2010-08-01 to 2015-07-31 of the following five asset class:

- US domestic equities (SPY: the S&P 500 stock index)
- US Treasury bonds (TLT)
- Investment-grade corporate bonds (LQD)
- Emerging-market equities (EEM)
- Real estate (VNQ)

Take a look at the first five rows.

```
mystocks = c("SPY", "TLT", "LQD", "EEM", "VNQ")
myprices = yahooSeries(mystocks, from='2010-08-01', to='2015-07-30')
head(myprices, 5)

## GMT
##            SPY.Open SPY.High SPY.Low SPY.Close SPY.Volume
SPY.Adj.Close
## 2010-08-02   111.99   112.94  111.54    112.76  188263200
101.8326
## 2010-08-03   112.48   112.77  111.85    112.22  146657300
101.3450
```

```
## 2010-08-04   112.53   113.11  112.16    112.97  158171700
102.0223
## 2010-08-05   112.25   112.91  112.08    112.85  140473800
101.9139
## 2010-08-06   111.74   112.57  110.92    112.39  239728300
101.4985
##            TLT.Open TLT.High TLT.Low TLT.Close TLT.Volume
TLT.Adj.Close
## 2010-08-02    99.24    99.33   98.75     98.75    5769200
84.60973
## 2010-08-03    99.20    99.66   98.93     99.32    4363500
85.09811
## 2010-08-04    99.50    99.51   98.56     98.56    3820400
84.44693
## 2010-08-05    99.34    99.49   98.84     99.02    3704200
84.84106
## 2010-08-06    99.79   100.21   99.49    100.10    6042400
85.76641
##            LQD.Open LQD.High LQD.Low LQD.Close LQD.Volume
LQD.Adj.Close
## 2010-08-02   109.91   109.95  109.56    109.63     764100
90.53107
## 2010-08-03   109.90   110.04  109.70    109.90    1060700
90.75404
## 2010-08-04   109.83   109.95  109.55    109.56     859900
90.47327
## 2010-08-05   109.69   109.89  109.59    109.76    1093400
90.63843
## 2010-08-06   110.19   110.48  110.06    110.39     685700
91.15867
##            EEM.Open EEM.High EEM.Low EEM.Close EEM.Volume
EEM.Adj.Close
## 2010-08-02    42.18    42.59   42.07     42.47   69623700
38.51627
## 2010-08-03    42.14    42.43   41.93     42.27   60207900
38.33489
## 2010-08-04    42.28    42.43   42.00     42.33   55875600
38.38930
## 2010-08-05    42.02    42.20   41.87     42.14   43650600
38.21699
## 2010-08-06    41.86    42.19   41.60     42.08   65731600
38.16258
##            VNQ.Open VNQ.High VNQ.Low VNQ.Close VNQ.Volume
VNQ.Adj.Close
## 2010-08-02    51.78    52.81   51.62     52.66    3018300
43.59576
## 2010-08-03    52.53    52.57   51.78     52.15    1955500
43.17355
## 2010-08-04    52.39    52.54   51.90     52.52    2041300
43.47986
```

```
## 2010-08-05    52.24    52.50   51.75     51.86    1847300
42.93346
## 2010-08-06    51.31    51.78   50.76     51.62    1836100
42.73477
```

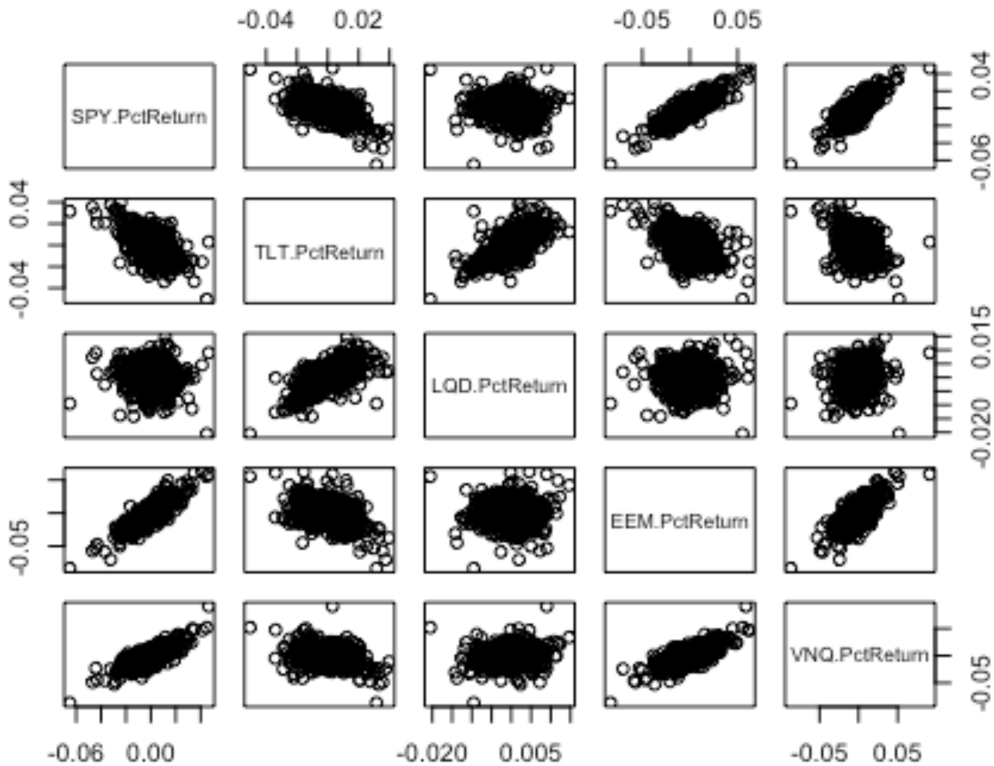
Since we are going to simulate a short-term (4 weeks) return, we would like to know the day to day return of five stocks using their close price. The following function calculate the

$$(P_t - P_{t-1})/P_{t-1}$$

```
YahooPricesToReturns = function(series) {
  mycols = grep('Adj.Close', colnames(series))
  closingprice = series[,mycols]
  N = nrow(closingprice)
  percentreturn = as.data.frame(closingprice[2:N,]) /
as.data.frame(closingprice[1:(N-1),]) - 1
  mynames = strsplit(colnames(percentreturn), '.', fixed=TRUE)
  mynames = lapply(mynames, function(x) return(paste0(x[1],
".PctReturn")))
  colnames(percentreturn) = mynames
  as.matrix(na.omit(percentreturn))
}
```

Use the function to get the day to day returns of the five portfolio we selected. Plot the correlation between each pairs of the five assets and print out the standard deviation of their day-to-day returns of each assets.

```
myreturns = YahooPricesToReturns(myprices)
pairs(myreturns)
```




```
apply(myreturns, 2, sd)

## SPY.PctReturn TLT.PctReturn LQD.PctReturn EEM.PctReturn
VNQ.PctReturn
##   0.009354486   0.009769863   0.003579966   0.013729404
0.011523419
```

From the plot of the returns, we can figure out the following fact:

- returns on SPY, EEM and VNQ are positively correlated
- returns on SPY and TLT are negatively correlated
- returns on TLT and LQD are positively correlated
- returns on LQD has no obviouse correlation with SPY, EEM and VNQ

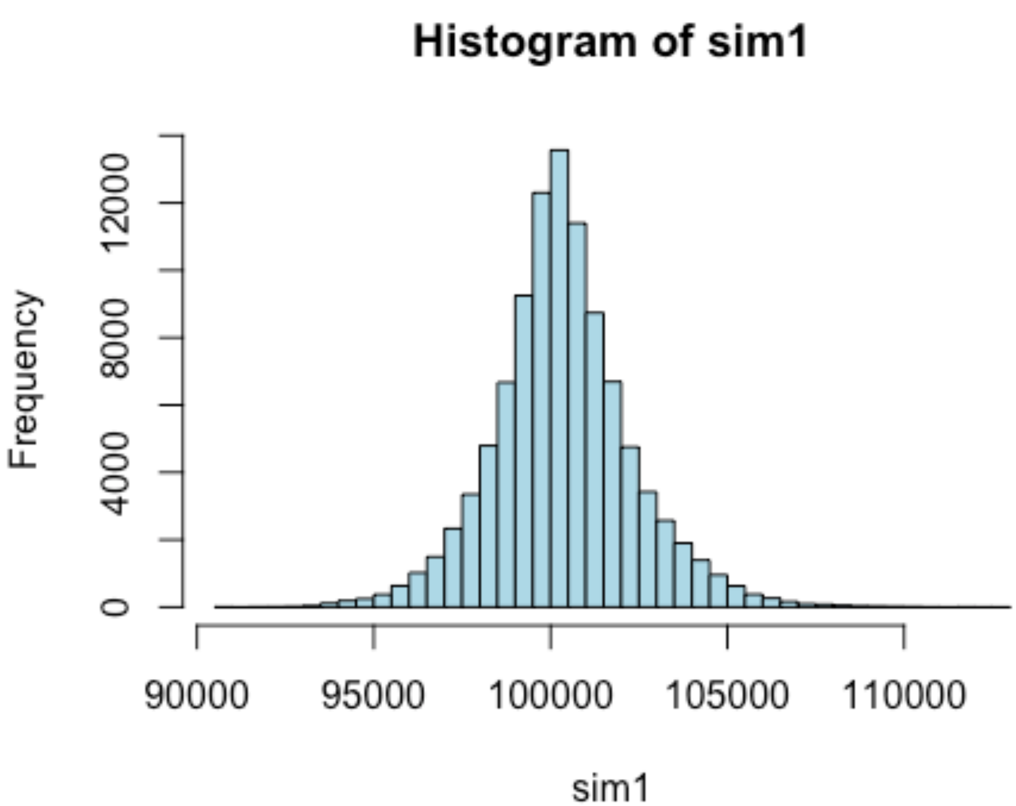
From the standard deviation of the returns, we can see that:

- EEM is the most risky assets, followed by VNQ
- LQD is the least risky assets

Evenly Split Portfolio

Simulation on evenly split portfolio, with weights being 0.2, 0.2, 0.2, 0.2, 0.2

```
sim1 = foreach(i = 1:5000, .combine = 'cbind')%do% {
  total_wealth = 100000
  weights = c(0.2, 0.2, 0.2, 0.2, 0.2)
  holdings = total_wealth * weights
  n_days = 20
  wealthtracker = rep(0, 20)
  for (today in 1:n_days) {
    return.today = resample(myreturns, 1, orig.ids = FALSE)
    holdings = holdings + holdings * return.today
    total_wealth = sum(holdings)
    wealthtracker[today] = total_wealth
  }
  wealthtracker
}

hist(sim1, 70, col = "Light Blue")
```



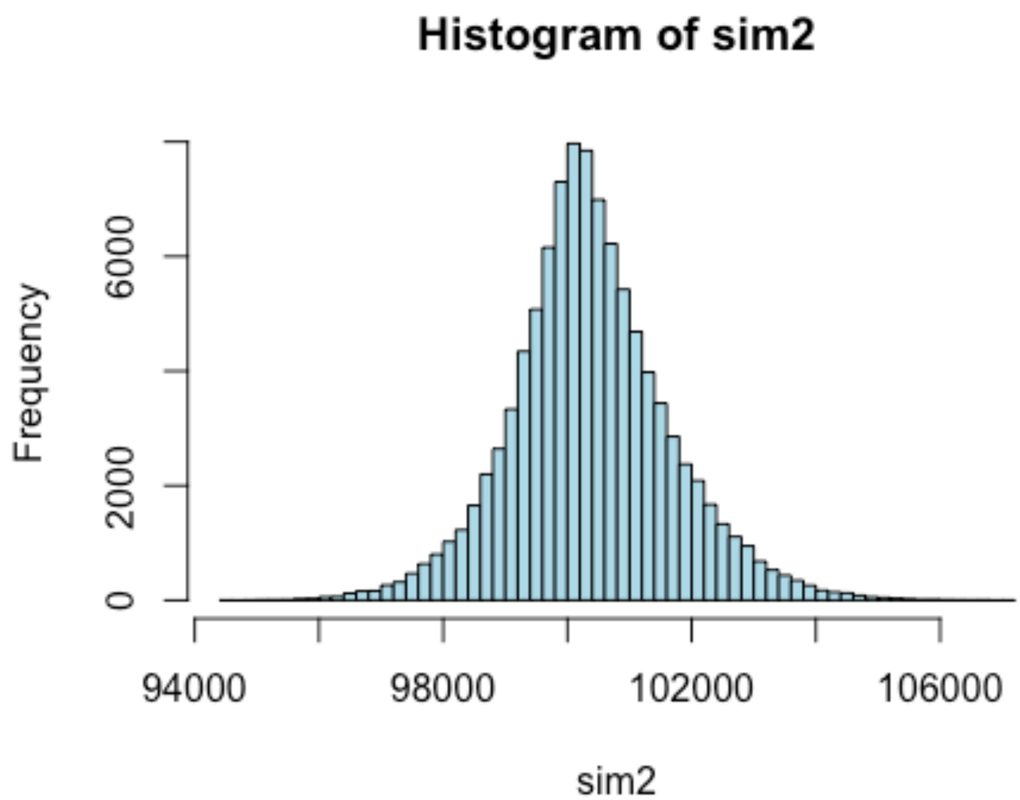

```
risk1 = quantile(sim1, 0.05) - 100000
risk1

##        5%
## -2792.256
```

A Safer Portfolio

Based on the above analysis of standard deviation and correlation, a safer portfolio than evenly split will be the one with SPY, TLT and LQD, because SPY and TLT have a comparative level of risk but negatively correlated, and LQD is the safest assets among all of the assets.

The following is the simulation of a safer portfilio with weights being 0.3, 0.3, 0.4, 0, 0

```
sim2 = foreach(i = 1:5000, .combine = 'cbind')%do% {
  total_wealth = 100000
  weights = c(0.3, 0.3, 0.4, 0, 0)
  holdings = total_wealth * weights
  n_days = 20
  wealthtracker = rep(0, 20)
  for (today in 1:n_days) {
    return.today = resample(myreturns, 1, orig.ids = FALSE)
    holdings = holdings + holdings * return.today
    total_wealth = sum(holdings)
    wealthtracker[today] = total_wealth
  }
  wealthtracker
}
hist(sim2, 60, col = "Light Blue")
```




```
risk2 = quantile(sim2, 0.05) - 100000
risk2

##        5%
## -1662.459
```

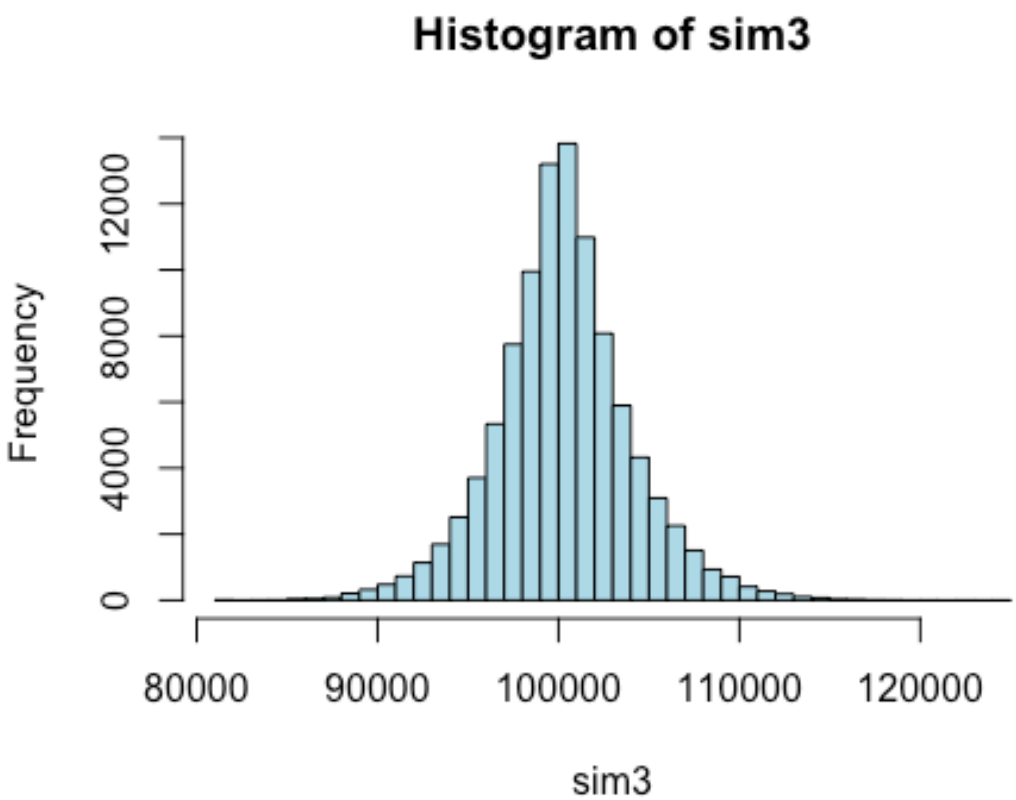
A More Aggressive Portfolio

Similarly, a more regressive portfolio than the evenly split one would include EEM, VNQ and SPY, since they are not only positively correlated to each other but also have relatively high risk.

The simulation is the following:

```
sim3 = foreach(i = 1:5000, .combine = 'cbind')%do% {
  total_wealth = 100000
  weights = c(0.2, 0, 0, 0.6, 0.2)
  holdings = total_wealth * weights
  n_days = 20
  wealthtracker = rep(0, 20)
  for (today in 1:n_days) {
    return.today = resample(myreturns, 1, orig.ids = FALSE)
    holdings = holdings + holdings * return.today
```

```
    total_wealth = sum(holdings)
    wealthtracker[today] = total_wealth
  }
  wealthtracker
}
hist(sim3, 60, col = "Light Blue")
```




```
risk3 = quantile(sim3, 0.05) - 100000
risk3

##         5%
## -5883.862
```

Now we have three options:

- The even split
  - 20% of your assets in each of the ETFs
  - The risk at 5% level is -2792.26.
- The safer option
  - 30% of your assets in SPY, 30% of you assets in TLT and the last 40% in LQD
  - The risk at 5% level is -1662.46.

- The more aggresive option
  - 20% of you assets in SPY, 20% of you assets in VNQ and the rest 60% in EEM
  - The risk at 5% level is -5883.86.

Clustering and PCA

Load the library and the data.

```
library(caret)
```

```
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:mosaic':
##
##     dotPlot
```

```
library(ggplot2)
library(cclust)
wines = read.csv('../data/wine.csv')
```

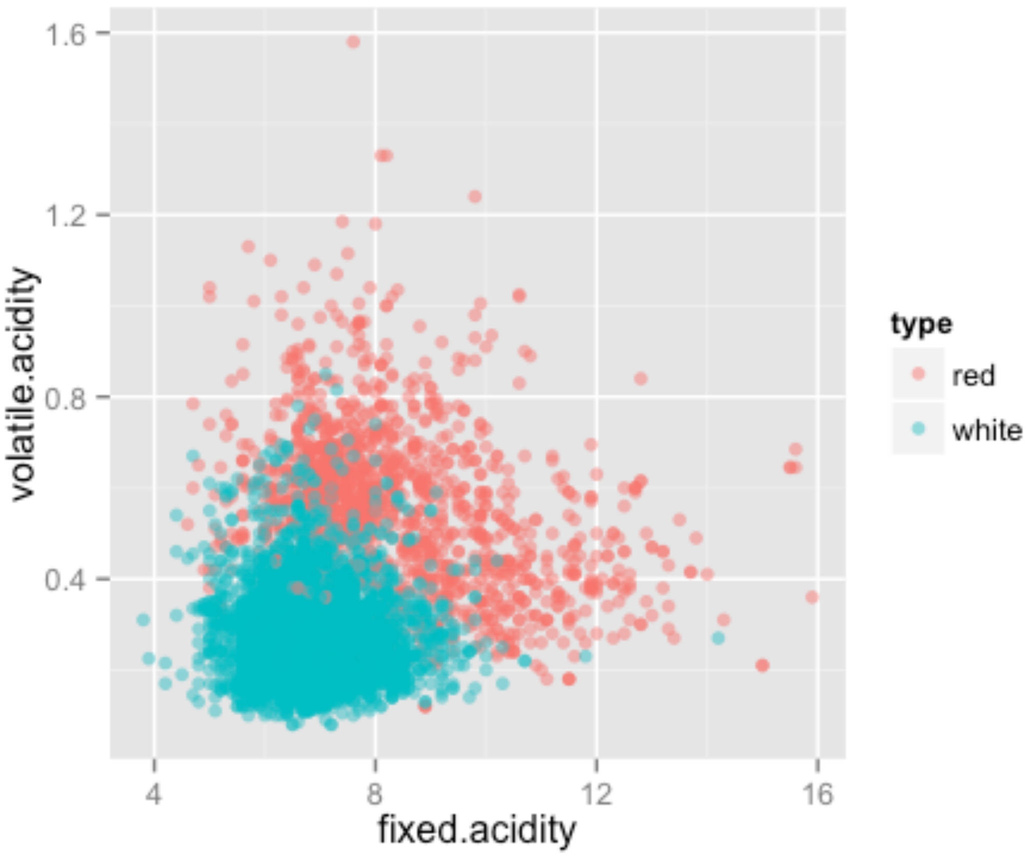
Summarize the data to see the columns. Remove the last two columns which are quality and color, since we are only clustering with the first 11 features. Scale the wine data.

```
wine = wines[, c(-12, -13)]
wine_scaled <- scale(wine, center = TRUE, scale = TRUE)
```

k-means clustering

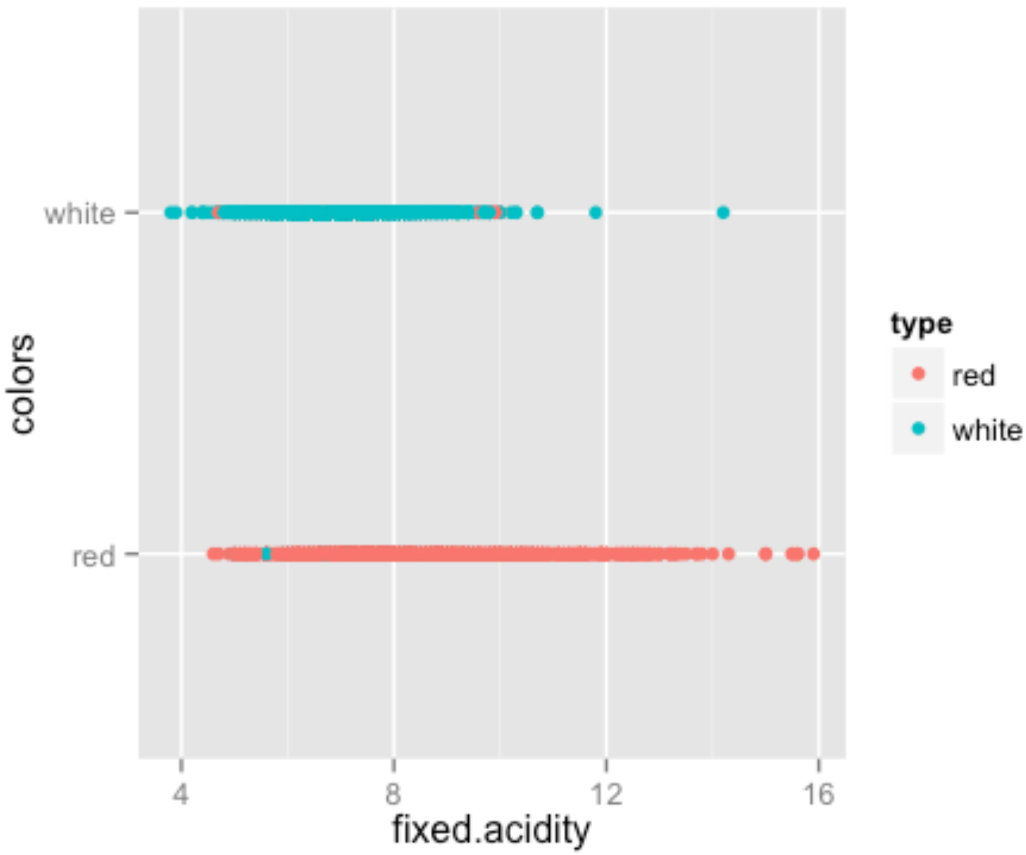
Since we know that we want two clusters seperating red and white wine, let's start with kmeans with 2 centers.

```
wine_kmean <- kmeans(wine_scaled, centers=2, nstart = 50)
type = ifelse(wine_kmean$cluster == 1, "white", "red")
qplot(wines$fixed.acidity, wines$volatile.acidity, col = type, xlab =
"fixed.acidity", ylab = "volatile.acidity", alpha = I(0.5))
```



The first plot shows the red wine tend to have lower level of both volatile acidity and fixed acidity. But it is unclear whether the red dots are truly red wine.

```
qplot(wines$fixed.acidity, wines$color, col = type, xlab =
"fixed.acidity", ylab = "colors")
```



This plot indicates the true classification of red and white wine in the y-axis, with the dots color representing the clustering result. Clearly, kmeans did a good job in clustering the color of the wine. Most red dots fall into the true red wine category, and most green dots fall into the true white wine category.

A confusion matrix can show us the accuracy of the classification.

```
confusionMatrix(type, wines$color)

## Confusion Matrix and Statistics
##
##             Reference
## Prediction   red white
##      red    1575    68
##      white    24  4830
##
##                Accuracy : 0.9858
##                  95% CI : (0.9827, 0.9886)
##     No Information Rate : 0.7539
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9622
##  Mcnemar's Test P-Value : 7.358e-06
```

```
##
##             Sensitivity : 0.9850
##             Specificity : 0.9861
##          Pos Pred Value : 0.9586
##          Neg Pred Value : 0.9951
##              Prevalence : 0.2461
##          Detection Rate : 0.2424
##    Detection Prevalence : 0.2529
##       Balanced Accuracy : 0.9856
##
##        'Positive' Class : red
##
```

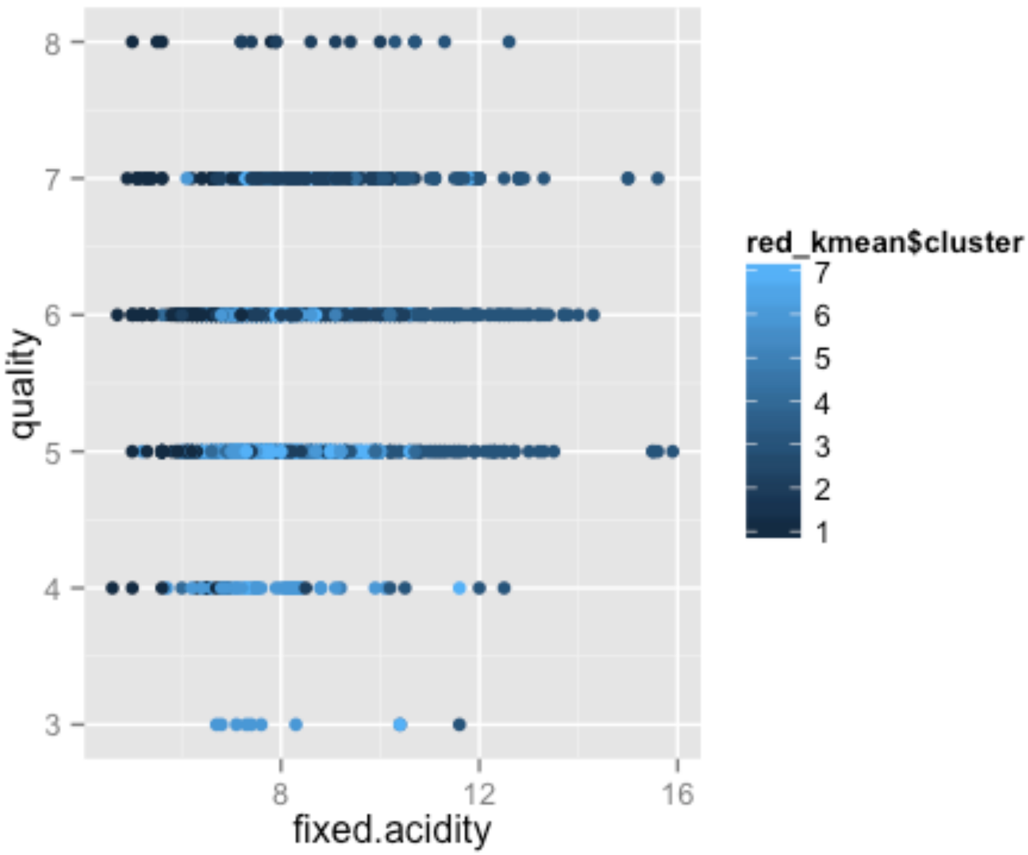
Of all the 1599 kinds of red wine, 24 of them were clustered to white wine. The accuracy of classifying red wine is around 98.5%. Of 4898 kinds of white wine, 68 of them are misclassified by kmeans, and the accuracy is 98.61%.

However, can they tell the difference between different wine quality? Let's split the data frame into two subset by their colors.

```
red = wines[wines$color == "red", ]
white = wines[wines$color == "white", ]
red_scaled = scale(red[, c(-12, -13)], center = TRUE, scale = TRUE)
white_scaled = scale(white[, c(-12, -13)], center = TRUE, scale = TRUE)
```

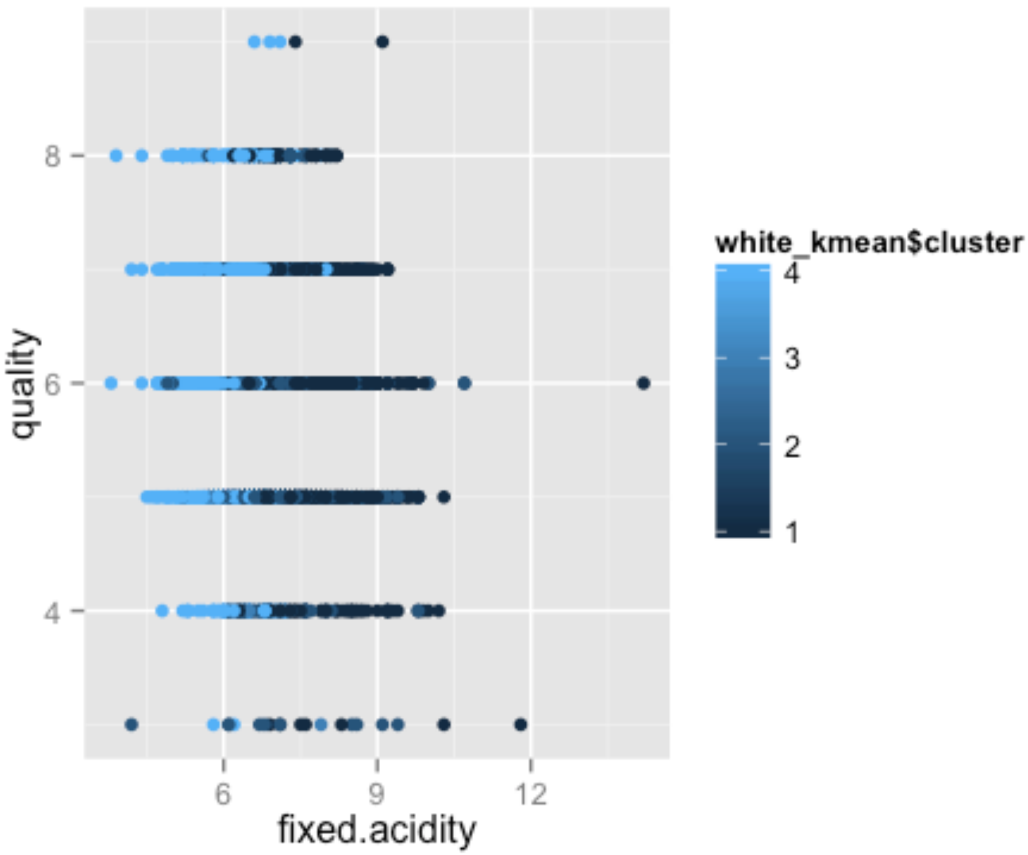
Try kmeans on each subset to see whether kmeans can rank them.

```
red_kmean <- kmeans(red_scaled, centers = 7, nstart = 100)
qplot(red$fixed.acidity, red$quality, col = red_kmean$cluster, xlab =
"fixed.acidity", ylab = "quality")
```



From the plot, we cannot see a clearly clustering by ranks. Try the same with white wine.

```
white_kmean <- kmeans(white_scaled, centers = 4, nstart = 100)
qplot(white$fixed.acidity, white$quality, col = white_kmean$cluster,
xlab = "fixed.acidity", ylab = "quality")
```



We still cannot tell the difference between each cluster in terms of their quality. It seems their quality are not determined by these 11 features.

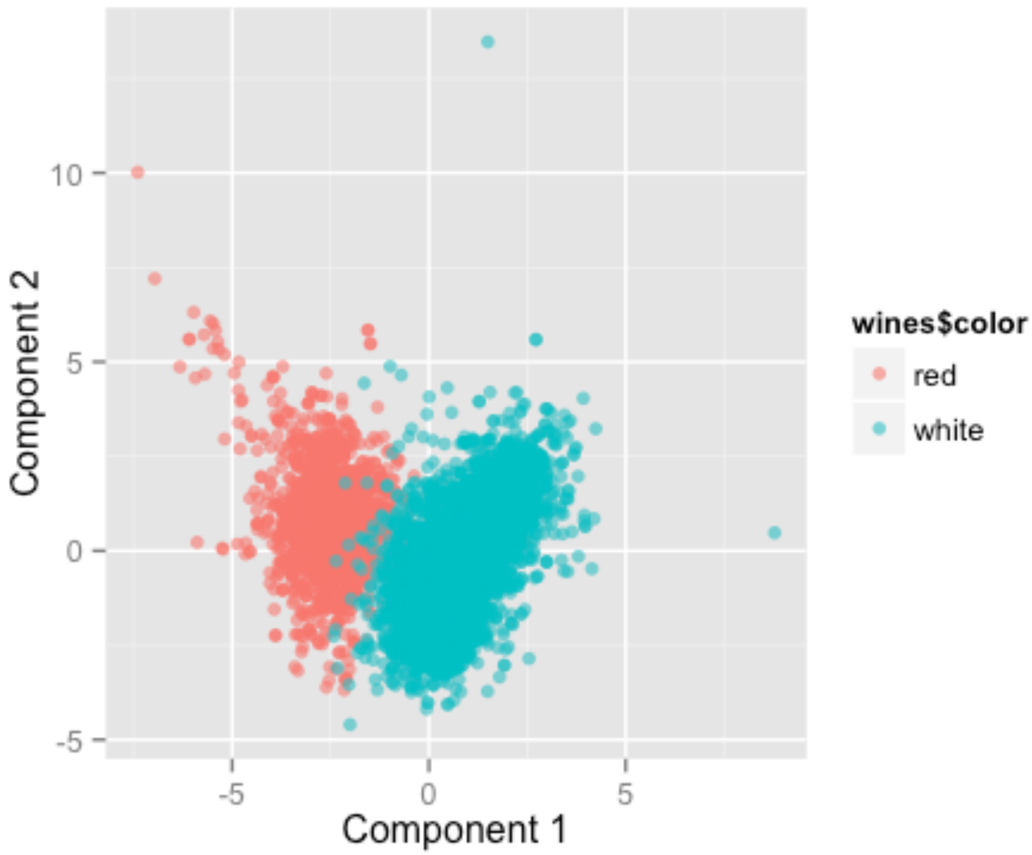
Principal Component Analysis

Apply PCA to the scaled wine data. Get the component vectors and the projection position on those vectors, named as scores.

```
wine_pca <- prcomp(wine_scaled)
loadings = wine_pca$rotation
scores = wine_pca$x
```

Plot the red and white wine with x being the first component and y being the second component.

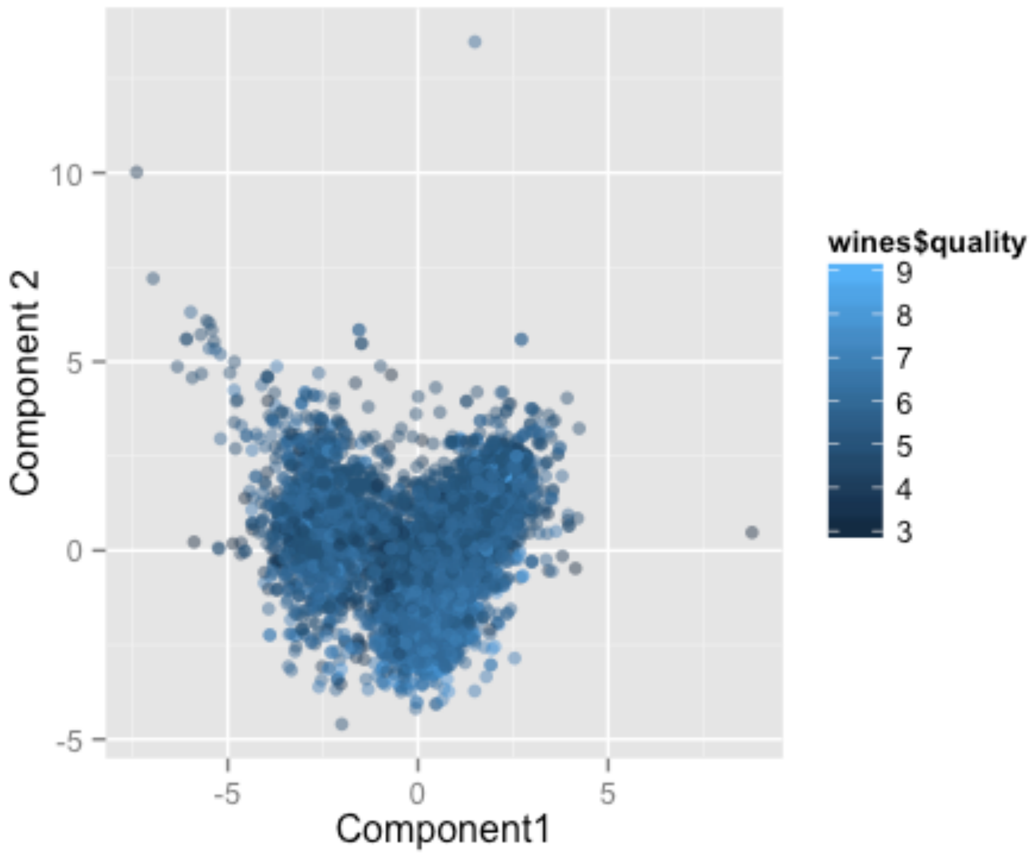
```
qplot(scores[,1], scores[,2], color=wines$color, xlab='Component 1',
ylab='Component 2', alpha = I(0.6))
```



Clearly, most kinds of wine, including both red and white, fall into the range of [-5, 5] in temrs of component 2. On the contrary, component 1 can seperate the two kinds of wine into two category. That is to say, component 1 itself is interesting enough in terms of telling the difference between wine color, while component 2 is does not provide much extra information. Since component 2 is not interesting to us, there's no need to consider the rest components.

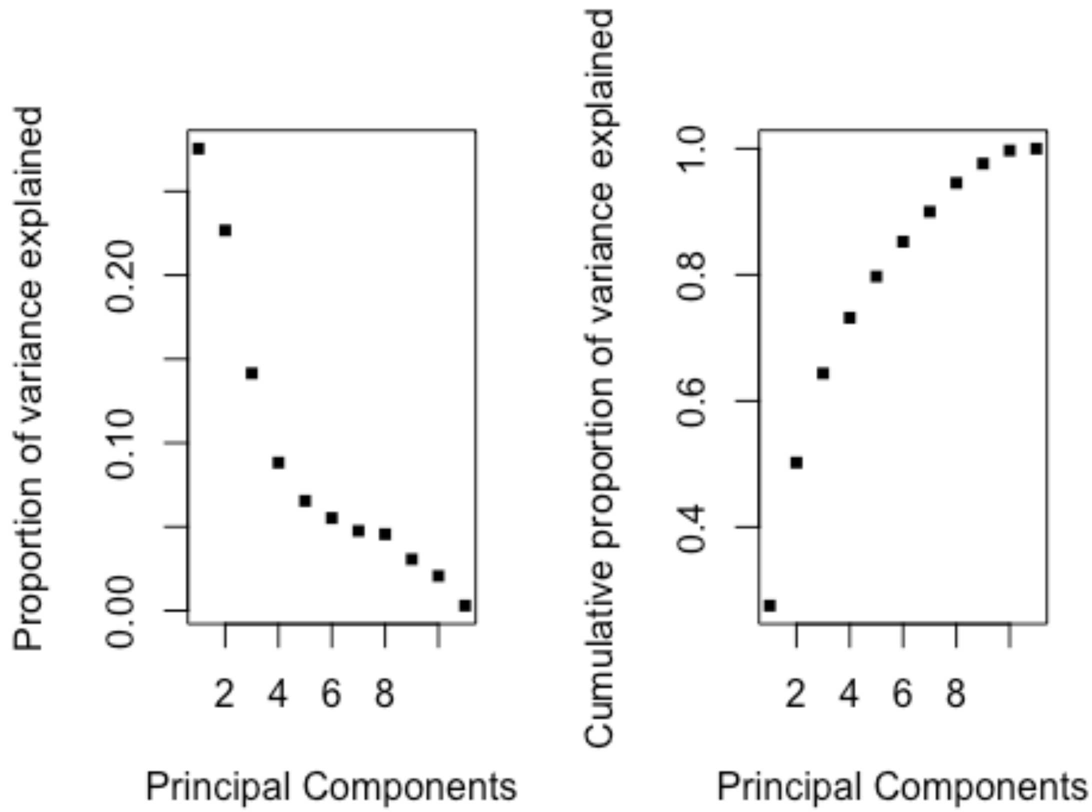
However, PCA doesn't seem work well when we want to know the scores of the wine. Let's take a look at the plot with color representing different scores.

```
qplot(scores[, 1], scores[, 2], color = wines$quality, xlab =
"Component1", ylab = "Component 2", alpha = I(0.5))
```



Even component 1 and component 2 together are not enough to order the quality of these wine.

```
vars <- (wine_pca$sdev)^2
sum <- sum(vars)
percent <- vars/sum
par(mfrow = c(1, 2))
plot(percent, xlab = "Principal Components", ylab = "Proportion of
variance explained", cex = 0.7, pch = 15, col = 9)
plot(cumsum(percent), xlab = "Principal Components", ylab = "Cumulative
proportion of variance explained", cex = 0.7, pch = 15, col = 9)
```




```
par(mfrow = c(1, 1))
```

The above two graph showed that the first two components explaine nearly 38% of the variance, and we need more components to rank the wine.

In conclusion, PCA works well in distinguishing red and white wine, but not in ranking the quality.

Market Segmentation

Load the library and the data. Take a look at the first row of the data set.

```
library(cluster)
market <- read.csv("../data/social_marketing.csv")
head(market, 1)

##             X chatter current_events travel photo_sharing
uncategorized
## 1 hmjoe4g3k       2              0      2             2
2
##   tv_film sports_fandom politics food family home_and_garden music
news
## 1       1             1        0    4      1               2     0
```

```
0
##   online_gaming shopping health_nutrition college_uni sports_playing
## 1             0        1               17           0              2
##   cooking eco computers business outdoors crafts automotive art
religion
## 1       5   1         1        0        2      1          0   0
1
##   beauty parenting dating school personal_fitness fashion
small_business
## 1      0         1      1      0               11       0
0
##   spam adult
## 1    0     0
```

We don't want the first column, "spam" column, "chatter" column and "uncategorized" column which does't provide interesting information about the user. So delete these columns.

Scale the data because some of the topic might be tweeted more often than others.

```
markets = market[, -1]
markets = markets[, -which(names(markets)=="spam")]
markets = markets[, -which(names(markets) == "chatter")]
markets = markets[, -which(names(markets) == "uncategorized")]
market_scaled <- scale(markets, center = TRUE, scale = TRUE)
```

Apply kmeans to the scaled data frame.

```
center_num = 8
segments <- kmeans(market_scaled, centers =  center_num, nstart = 100)
```

Take a look at the clustering centers.

```
segments$centers

##   current_events      travel photo_sharing     tv_film sports_fandom
## 1     0.10234034 -0.11272269  -0.025459271 -0.10705254     2.0249394
## 2    -0.09330702 -0.22207450  -0.147276970 -0.22458904    -0.3147726
## 3     0.01025367 -0.15952768   0.002424409 -0.15545129    -0.2087017
## 4     0.11780919  3.19186654  -0.057575455 -0.07686805    -0.2181462
## 5     0.08895021 -0.18557373  -0.126954494 -0.03844082     0.6355539
## 6     0.31876161  0.20430462   0.058709428  2.64827640    -0.1106166
## 7     0.17632541 -0.05991035   1.279706183 -0.14787147    -0.2099234
## 8    -0.05862658 -0.04421146   0.026826191  0.09302734    -0.1325942
##     politics        food      family home_and_garden        music
## 1 -0.2238752  1.80041211  1.45616807      0.15771029  0.032279123
## 2 -0.2838071 -0.37481987 -0.26822345     -0.13468126 -0.180055714
## 3 -0.1921082  0.41922856 -0.07854314      0.14777257  0.002940299
## 4  3.0479280  0.14597546 -0.09151735      0.04035434 -0.045743648
## 5  1.1907155 -0.17611672  0.23536706      0.13717972 -0.079069871
## 6 -0.0952232  0.09674490 -0.12442881      0.29806205  1.088913110
## 7 -0.1269455 -0.20220491  0.04039369      0.13899567  0.535429228
```

```
## 8 -0.1622641 -0.09285402  0.20046769      0.06992411 -0.033867664
##          news online_gaming    shopping health_nutrition college_uni
## 1 -0.12730023   -0.08179991  0.06534396      -0.15583728 -0.13316289
## 2 -0.31671659   -0.22630957 -0.06882735      -0.32254820 -0.24471756
## 3 -0.09113928   -0.11565666  0.04981961       2.12456190 -0.20787115
## 4  1.11359940   -0.15476099 -0.01792300      -0.16009949 -0.03918070
## 5  2.56887531   -0.13999124 -0.07224083      -0.26347758 -0.19941660
## 6  0.01240974   -0.17354869  0.20355939      -0.18248717  0.40952284
## 7 -0.08776632   -0.03405535  0.32163363      -0.06799234 -0.02106146
## 8 -0.20220246    3.50100087 -0.07483086      -0.18919863  3.23523662
##   sports_playing    cooking         eco   computers    business
## 1     0.10056064 -0.1045525  0.20113505  0.08527873  0.10986672
## 2    -0.23189096 -0.3242998 -0.17290368 -0.22056362 -0.14703738
## 3    -0.02790323  0.3778584  0.54068822 -0.06625756  0.07953593
## 4     0.02910975 -0.1837864  0.18755952  2.88959887  0.55359376
## 5    -0.08695907 -0.2504689 -0.05835230 -0.19827530 -0.08066612
## 6     0.11915055 -0.1629270  0.11899003 -0.15024959  0.41722581
## 7     0.20034251  2.6867046  0.04897007  0.07089596  0.26084461
## 8     2.07471923 -0.1327845 -0.04725155 -0.09012065 -0.09767463
##      outdoors      crafts  automotive          art    religion
## 1 -0.08188459  0.68362688  0.11849451 -0.021052780  2.21225549
## 2 -0.32975938 -0.22612614 -0.25185210 -0.235468568 -0.30720507
## 3  1.62876906  0.05306240 -0.15349796 -0.086522057 -0.17410994
## 4 -0.03883854  0.21241954 -0.12677206 -0.162205164  0.10385816
## 5  0.28214013 -0.15514338  2.54644636 -0.175312889 -0.20195616
## 6 -0.09591099  0.68543839 -0.18441845  2.381751806 -0.00347951
## 7  0.02545895  0.10536135  0.03726068 -0.002247328 -0.12916572
## 8 -0.14970455  0.02968489  0.06190603  0.267316090 -0.18946174
##         beauty    parenting       dating      school
personal_fitness
## 1  0.305945440  2.097901478  0.047234325  1.65058671      -
0.11147215
## 2 -0.270679450 -0.307765427 -0.087044097 -0.26053041      -
0.32948234
## 3 -0.215850225 -0.103591777  0.186560834 -0.15178486
2.07725967
## 4 -0.182193847  0.008753798  0.368607935 -0.08655386      -
0.14112898
## 5 -0.182323209  0.020347760 -0.018290108  0.01254789      -
0.24904831
## 6 -0.006161053 -0.198057182 -0.047868942 -0.01216216      -
0.15881086
## 7  2.533378051 -0.067382729  0.119065896  0.20358928      -
0.04259446
## 8 -0.233020861 -0.147475858 -0.004293009 -0.19153363      -
0.19210751
##       fashion small_business         adult
## 1  0.02218561     0.09453593  1.348903e-02
## 2 -0.26196120    -0.14389108  1.964096e-02
## 3 -0.11033219    -0.10790216 -2.288329e-05
```

```
## 4 -0.15609324     0.40802588 -1.157275e-01
## 5 -0.22046241    -0.13263537 -8.934443e-02
## 6 -0.02180280     0.82502146 -2.307904e-02
## 7  2.59660035     0.20254493  1.301350e-02
## 8 -0.06539505     0.10904749 -8.615448e-03
```

Unscale the data and get mu and sigma.

```
mu = attr(market_scaled,"scaled:center")
sigma = attr(market_scaled,"scaled:scale")
segments_unscaled = segments$centers * sigma + mu
```

First Cluster

```
rbind(segments$centers[1, ], segments_unscaled[1, ])
```

```
##      current_events     travel photo_sharing    tv_film
sports_fandom
## [1,]      0.1023403 -0.1127227   -0.02545927 -0.1070525
2.024939
## [2,]      1.6561210  0.4376382    1.91090001  0.8904199
4.075406
##        politics     food   family home_and_garden      music
news
## [1,] -0.2238752 1.800412 1.456168       0.1577103 0.03227912 -
0.1273002
## [2,]  0.6103146 2.395510 3.097752       0.4338241 1.45480138
1.1806714
##      online_gaming   shopping health_nutrition college_uni
sports_playing
## [1,]   -0.08179991 0.06534396       -0.1558373  -0.1331629
0.1005606
## [2,]    0.71811450 1.11605018        1.3162718   1.9685223
0.5980016
##         cooking       eco  computers  business    outdoors    crafts
## [1,] -0.1045525 0.2011351 0.08527873 0.1098667 -0.08188459 0.6836269
## [2,]  1.2105911 2.0286479 1.54362427 0.9155513  0.67039844 2.2042756
##      automotive         art religion    beauty parenting     dating
## [1,]  0.1184945 -0.02105278 2.212255 0.3059454  2.097901 0.04723433
## [2,]  1.5272801  0.40866633 4.653867 3.5324705  5.612761 0.70478452
##        school personal_fitness    fashion small_business      adult
## [1,] 1.650587       -0.1114721 0.02218561     0.09453593 0.01348903
## [2,] 3.422570        1.3302309 0.70212073     0.58507318 0.72306310
```

Clearly, people who fall into the first cluster loves to tweet about online games, college unions, and sports playing. They are more likely to be male students in college who love games and sports.

Second Cluster

```
rbind(segments$centers[2, ], segments_unscaled[2, ])
```

```
##      current_events     travel photo_sharing    tv_film
sports_fandom
## [1,]    -0.09330702 -0.2220745    -0.1472770 -0.2245890    -
0.3147726
## [2,]     1.37174786  0.4505292     0.3989438  0.4069186
1.1268504
##        politics       food     family home_and_garden      music
## [1,] -0.2838071 -0.3748199 -0.2682235      -0.1346813 -0.1800557
## [2,]  0.3116018  0.7126138  0.5818051       0.1590893  0.6599428
##            news online_gaming    shopping health_nutrition
college_uni
## [1,] -0.3167166    -0.2263096 -0.06882735       -0.3225482  -
0.2447176
## [2,]  0.3302155     0.3560275  0.29379055        0.8247851
0.8404953
##      sports_playing    cooking        eco  computers   business
outdoors
## [1,]     -0.2318910 -0.3242998 -0.1729037 -0.2205636 -0.1470374 -
0.3297594
## [2,]      0.5130675  0.4036207  1.2645416  1.5755560  0.3957518
0.6689136
##          crafts automotive        art   religion     beauty
parenting
## [1,] -0.2261261 -0.2518521 -0.2354686 -0.3072051 -0.2706794 -
0.3077654
## [2,]  1.1053717  0.9338065  0.4978742  0.4026593  0.6212882
0.3817215
##          dating     school personal_fitness    fashion
small_business
## [1,] -0.0870441 -0.2605304       -0.3294823 -0.2619612     -
0.1438911
## [2,]  0.3629753  0.2465046        1.7967932  0.6552087
0.4793610
##           adult
## [1,] 0.01964096
## [2,] 0.95110285
```

People in the second cluster loves to talk about food, sports_fandon, family , crafts, religious, parenting and schooling. They seems to be father with one or two children.

Third Cluster

```
rbind(segments$centers[3, ], segments_unscaled[3, ])
```

```
##      current_events     travel photo_sharing    tv_film
sports_fandom
## [1,]     0.01025367 -0.1595277   0.002424409 -0.1554513    -
0.2087017
## [2,]     2.72478547  0.8703990   0.651933316  0.6857753
```

```
1.1080100
##         politics      food      family home_and_garden       music
## [1,] -0.1921082 0.4192286 -0.07854314       0.1477726 0.002940299
## [2,]  0.4813949 0.8349972  0.60085332       1.7137696 0.522846123
##              news online_gaming   shopping health_nutrition
college_uni
## [1,] -0.09113928    -0.1156567 0.04981961         2.124562  -
0.2078711
## [2,]  1.68562146     0.8739445 0.49366830         3.270065
0.4363961
##      sports_playing   cooking       eco   computers   business
outdoors
## [1,]    -0.02790323 0.3778584 0.5406882 -0.06625756 0.07953593
1.628769
## [2,]     0.67934561 0.5699079 2.3575109  1.35752145 0.93852361
3.974636
##         crafts automotive         art   religion     beauty
parenting
## [1,] 0.0530624  -0.153498 -0.08652206 -0.1741099 -0.2158502 -
0.1035918
## [2,] 1.9494705   1.877093  0.44518359  1.0432886  1.1275771
1.2019866
##         dating     school personal_fitness    fashion small_business
## [1,] 0.1865608 -0.1517849          2.07726 -0.1103322     -0.1079022
## [2,] 1.0083115  0.5873388          4.51601  0.9123164      0.3485336
##              adult
## [1,] -2.288329e-05
## [2,]  7.108194e-01
```

People in the third cluster love to tweet things about travelling, poiltics, news, computers. They seems to be professionals who have to travel a lot.

Forth Cluster

```
rbind(segments$centers[4, ], segments_unscaled[4, ])
```

```
##      current_events   travel photo_sharing     tv_film sports_fandom
## [1,]      0.1178092 3.191867   -0.05757546 -0.07686805    -0.2181462
## [2,]      1.2657066 9.786859    0.38337880  0.57385466     2.1009090
##      politics      food      family home_and_garden       music
news
## [1,] 3.047928 0.1459755 -0.09151735      0.04035434 -0.04574365
1.113599
## [2,] 7.608558 0.8212451  0.78265817      1.67723484  0.63215259
1.369472
##      online_gaming  shopping health_nutrition college_uni
sports_playing
## [1,]    -0.1547610 -0.017923       -0.1600995  -0.0391807
0.02910975
## [2,]     0.4996434  1.503520        0.4027361   1.8638363
```

```
1.15114747
##           cooking       eco computers  business    outdoors    crafts
## [1,] -0.18378638 0.1875595  2.889599 0.5535938 -0.03883854 0.2124195
## [2,]  0.07004068 1.0762898  3.458030 1.6269389  0.31232804 1.7746510
##      automotive        art  religion     beauty   parenting
dating
## [1,] -0.1267721 -0.1622052 0.1038582 -0.1821938 0.008753798
0.3686079
## [2,]  1.1822016  0.6082688 1.1864700  1.2363821 2.606600155
0.8169554
##            school personal_fitness    fashion small_business
adult
## [1,] -0.08655386        -0.141129 -0.1560932      0.4080259 -
0.1157275
## [2,]  1.25388230         1.289044  1.1070196      1.2761697
0.6301842
```

People in this cluster like photo sharing, cooking, shopping, beauty things and fashion. Clearly, they are more likely to be young ladies.

Fifth Cluster

```r
rbind(segments$centers[5, ], segments_unscaled[5, ])
```

```
##      current_events     travel photo_sharing     tv_film
sports_fandom
## [1,]     0.08895021 -0.1855737    -0.1269545 -0.03844082
0.6355539
## [2,]     1.78622573  1.0536939     0.6291201  0.72202090
2.1245330
##      politics       food     family home_and_garden       music
news
## [1,] 1.190715 -0.1761167 0.2353671       0.1371797 -0.07906987
2.568875
## [2,] 4.408836  0.3013033 1.1303659       3.0714852  1.03942317
3.678942
##      online_gaming    shopping health_nutrition college_uni
sports_playing
## [1,]    -0.1399912 -0.07224083       -0.2634776  -0.1994166    -
0.08695907
## [2,]     0.7092028  1.41989526        0.4078834   0.3588106
0.58967778
##         cooking        eco   computers    business   outdoors
crafts
## [1,] -0.2504689 -0.0583523 -0.1982753 -0.08066612 0.2821401 -
0.1551434
## [2,]  1.2084448  0.4776924  1.3181513  0.94094539 0.9149648
0.6881576
##      automotive        art   religion     beauty   parenting
dating
```

```
## [1,]   2.546446 -0.1753129 -0.2019562 -0.1823232 0.02034776 -
0.01829011
## [2,]   3.123279  0.4391304  0.2114974  1.0737626 1.60843043
0.80487847
##          school personal_fitness    fashion small_business
adult
## [1,] 0.01254789       -0.2490483 -0.2204624     -0.1326354 -
0.08934443
## [2,] 1.01951719        1.0337386  1.5760111      0.4075160
1.24717030
```

This group like to talk about home and gardening, health and nutrition, eco-friendly, outdoor activities and personal fitness. They care about health and environment!

Sixth Cluster

```
rbind(segments$centers[6, ], segments_unscaled[6, ])
```

```
##      current_events    travel photo_sharing  tv_film sports_fandom
## [1,]      0.3187616 0.2043046    0.05870943 2.648276    -0.1106166
## [2,]      2.7548349 3.4858248    0.56381557 7.831817     1.3549784
##        politics      food     family home_and_garden    music
news
## [1,] -0.0952232 0.0967449 -0.1244288       0.2980621 1.088913
0.01240974
## [2,]  1.2171241 0.8996807  0.6198449       1.5647071 4.135246
0.43183508
##      online_gaming  shopping health_nutrition college_uni
sports_playing
## [1,]    -0.1735487 0.2035594       -0.1824872   0.4095228
0.1191506
## [2,]     0.4015362 3.2528020        0.8221662   1.1320869
1.1018956
##        cooking       eco  computers  business    outdoors    crafts
## [1,] -0.162927 0.1189900 -0.1502496 0.4172258 -0.09591099 0.6854384
## [2,]  1.212629 0.8018307  0.3966557 1.2591863  1.40456183 1.0256365
##      automotive      art    religion       beauty  parenting
dating
## [1,] -0.1844184 2.381752 -0.00347951 -0.006161053 -0.1980572 -
0.04786894
## [2,]  1.3656794 5.656056  0.39701419  0.856889265  0.4459697
0.64680998
##           school personal_fitness    fashion small_business
adult
## [1,] -0.01216216       -0.1588109 -0.0218028      0.8250215 -
0.02307904
## [2,]  0.32881795        1.1155102  1.4863137      1.9569694
0.95437648
```

People from this group love to talk about current events, tv and film, about music, about art and small business. These people are those fantastic artists, musicians, movie makers!

Seventh Cluster

```
rbind(segments$centers[7, ], segments_unscaled[7, ])
```

```
##      current_events      travel photo_sharing    tv_film
sports_fandom
## [1,]      0.1763254 -0.05991035      1.279706 -0.1478715    -
0.2099234
## [2,]      1.7105638  1.37591028      2.578137  0.7262044
1.1523308
##        politics       food      family home_and_garden     music
## [1,] -0.1269455 -0.2022049 0.04039369       0.1389957 0.5354292
## [2,]  1.9964766  0.3506883 1.55922214       1.8943698 2.3578771
##             news online_gaming  shopping health_nutrition
college_uni
## [1,] -0.08776632   -0.03405535 0.3216336      -0.06799234 -
0.02106146
## [2,]  0.67651751    0.72723197 1.6038072       1.02610322
0.40866032
##      sports_playing   cooking        eco  computers  business
outdoors
## [1,]      0.2003425  2.686705 0.04897007 0.07089596 0.2608446
0.02545895
## [2,]      1.0679400 10.035538 1.30840694 0.73269231 1.3166129
1.64319099
##         crafts automotive          art   religion   beauty
parenting
## [1,] 0.1053613 0.03726068 -0.002247328 -0.1291657 2.533378 -
0.06738273
## [2,] 0.7877930 0.54098699  0.702166744  1.3623652 2.386998
1.76710503
##         dating    school personal_fitness  fashion small_business
## [1,] 0.1190659 0.2035893      -0.04259446 2.596600      0.2025449
## [2,] 1.3233981 0.7725185       0.81562618 3.172205      1.0548783
##          adult
## [1,] 0.0130135
## [2,] 0.3443802
```

People from this group usually talk about news and automotives. These people probably care more about cars news.

Eighth Cluster

```
rbind(segments$centers[8, ], segments_unscaled[8, ])
```

```
##      current_events      travel photo_sharing    tv_film
sports_fandom
```

```
## [1,]    -0.05862658 -0.04421146    0.02682619 0.09302734    -
0.1325942
## [2,]     0.79746881  0.59604885    0.76853134 0.39384051
1.1620594
##        politics        food    family home_and_garden       music
## [1,] -0.1622641 -0.09285402 0.2004677      0.06992411 -0.03386766
## [2,]  1.0793757  0.70301291 1.3631121      2.00058025  2.41496792
##            news online_gaming    shopping health_nutrition
college_uni
## [1,] -0.2022025      3.501001 -0.07483086       -0.1891986
3.235237
## [2,]  0.3506903      9.882827  1.43230837        1.0471370
4.695633
##      sports_playing    cooking         eco   computers    business
## [1,]       2.074719 -0.1327845 -0.04725155 -0.09012065 -0.09767463
## [2,]       3.233003  0.8500260  1.08184337  0.36084519  0.53677011
##        outdoors     crafts automotive       art   religion
beauty
## [1,] -0.1497045 0.02968489 0.06190603 0.2673161 -0.1894617 -
0.2330209
## [2,]  2.2878580 1.26789303 0.72208911 1.3264195  1.1519834
0.4392543
##       parenting       dating     school personal_fitness     fashion
## [1,] -0.1474759 -0.004293009 -0.1915336       -0.1921075 -0.06539505
## [2,]  0.3987907  0.699450278  1.2832272        0.3791561  1.77392264
##      small_business        adult
## [1,]      0.1090475 -0.008615448
## [2,]      1.3042146  0.387700535
```

Well, these people don't tweet a lot. But when they tweet, they tweet about adult things. And they seems to have little interest in other topics. So, they are probaly single males.