Exercise1

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(1)Explanatory Analysis

Does using certain kinds of voting equipment lead to higher rates of undercount?

Read in data and create new column for the amount of undercounted votes

```
votes = read.csv('georgia2000.csv', header = TRUE)
summary(votes)
```

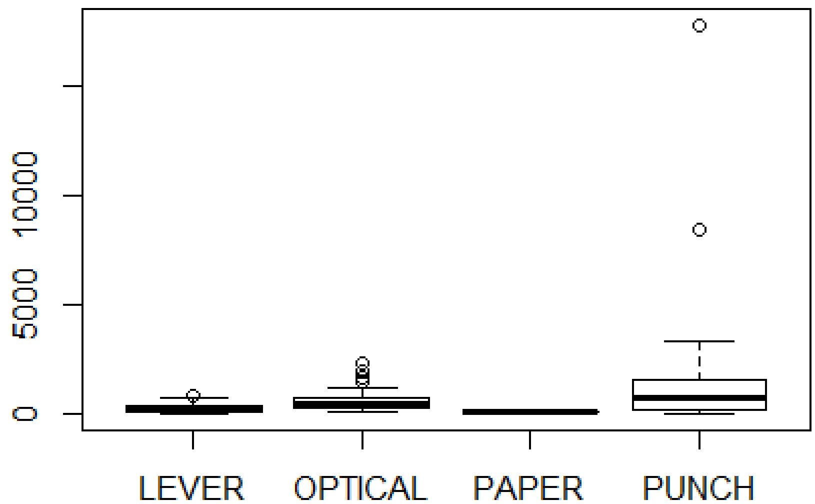
```
##       county       ballots           votes             equip   
##  APPLING :  1   Min.   :   881   Min.   :   832   LEVER  :74  
##  ATKINSON:  1   1st Qu.:  3694   1st Qu.:  3506   OPTICAL:66  
##  BACON   :  1   Median :  6712   Median :  6299   PAPER  : 2  
##  BAKER   :  1   Mean   : 16927   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  
## 
```

```
votes$undercount = votes$ballots - votes$votes
summary(votes$undercount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##     0.0   152.5   296.0   595.5   523.5 17760.0
```

Boxplot Undercount against equipment. Lever and Paper are extremely accurate, while optical and punch are less reliable

```
boxplot(undercount~equip, data = votes)
```




```
lm.fit = glm(undercount~equip, data = votes)
summary(lm.fit)

## 
## Call:
## glm(formula = undercount ~ equip, data = votes)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -2260.5   -246.8   -110.9    116.1  15501.5  
## 
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)    
## (Intercept)      229.9      171.9   1.338    0.183    
## equipOPTICAL     362.3      250.3   1.447    0.150    
## equipPAPER      -173.4     1059.5  -0.164    0.870    
## equipPUNCH      2032.5      397.7   5.111 9.32e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for gaussian family taken to be 2186205)
## 
```

```
##     Null deviance: 396571504  on 158  degrees of freedom
## Residual deviance: 338861726  on 155  degrees of freedom
## AIC: 2778.2
##
## Number of Fisher Scoring iterations: 2
```

If so, should we worry that this effect has a disparate impact on poor and minority communities?

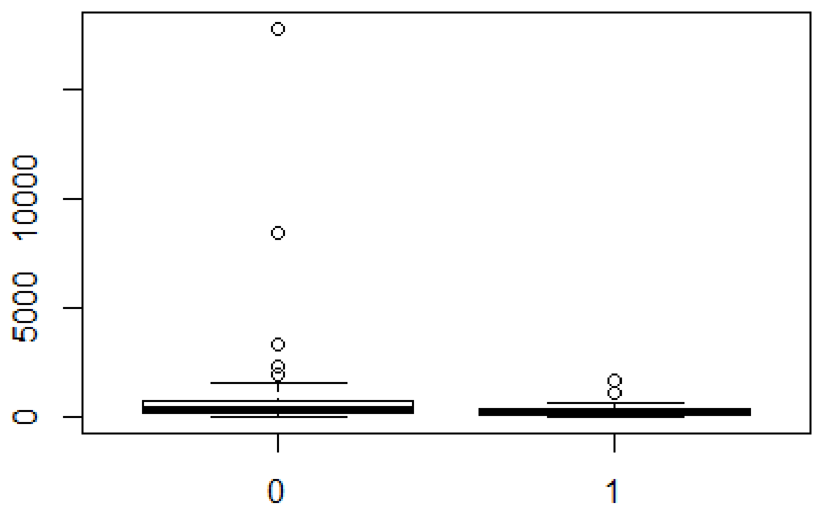
Xtab and Boxplot show that the poor have on average less undercounting and the large outliers pertain to the rich.

```
x1 = xtabs(~undercount + poor, data = votes)
x1

##           poor
## undercount 0 1
##       0    1 1
##       2    0 1
##       20   1 0
##       23   1 0
##       27   0 1
##       35   1 0
##       41   0 1
##       49   0 1
##       52   0 1
##       56   0 1
##       57   0 1
##       64   0 1
##       65   2 2
##       67   1 0
##       70   0 1
##       78   0 2
##       80   0 1
##       81   0 1
##       85   1 0
##       88   0 2
##       102  1 0
##       105  1 0
##       107  0 1
##       110  1 0
##       111  0 1
##       113  0 1
##       118  1 0
##       119  0 1
##       123  1 1
##       124  1 1
##       136  1 0
##       147  0 1
##       158  0 1
```

```
##       159   0 1
##       166   0 1
##       167   0 1
##       169   0 1
##       170   1 0
##       171   0 1
##       176   1 0
##       178   0 1
##       181   0 1
##       193   1 0
##       195   2 0
##       197   0 1
##       201   1 0
##       203   0 1
##       205   0 2
##       213   0 1
##       216   1 0
##       217   1 0
##       222   1 0
##       235   0 1
##       236   0 1
##       240   1 0
##       241   1 0
##       243   1 0
##       244   0 1
##       246   2 0
##       248   0 1
##       250   0 1
##       257   1 0
##       261   1 0
##       265   1 0
##       269   0 1
##       272   1 0
##       282   0 1
##       295   1 0
##       296   1 1
##       297   1 0
##       301   1 0
##       304   0 1
##       307   0 1
##       317   1 0
##       330   1 0
##       336   0 1
##       338   0 1
##       344   0 1
##       345   1 0
##       346   1 0
##       348   0 1
##       352   0 1
##       353   0 2
```

```
##       362   1 1
##       364   0 1
##       370   1 0
##       383   0 1
##       393   1 0
##       397   0 1
##       404   1 0
##       407   1 0
##       413   1 0
##       415   0 1
##       420   1 0
##       421   1 0
##       442   1 0
##       452   0 1
##       457   0 1
##       469   0 1
##       475   0 1
##       479   1 0
##       492   0 1
##       493   0 1
##       509   1 0
##       518   0 1
##       529   0 1
##       552   1 0
##       589   1 0
##       615   1 0
##       618   0 1
##       655   0 1
##       659   1 0
##       675   1 0
##       686   1 0
##       687   1 0
##       694   1 0
##       702   1 0
##       719   1 0
##       739   1 0
##       759   1 0
##       767   1 0
##       782   1 0
##       786   1 0
##       879   1 0
##       955   1 0
##       980   1 0
##       984   1 0
##       995   1 0
##       999   1 0
##       1080  0 1
##       1097  1 0
##       1110  1 0
##       1151  1 0
```

```
##       1193  1 0
##       1323  1 0
##       1499  1 0
##       1598  1 0
##       1688  0 1
##       1907  1 0
##       1911  1 0
##       2299  1 0
##       2308  1 0
##       3366  1 0
##       8372  1 0
##       17764 1 0

boxplot(undercount~poor, data = votes)
```

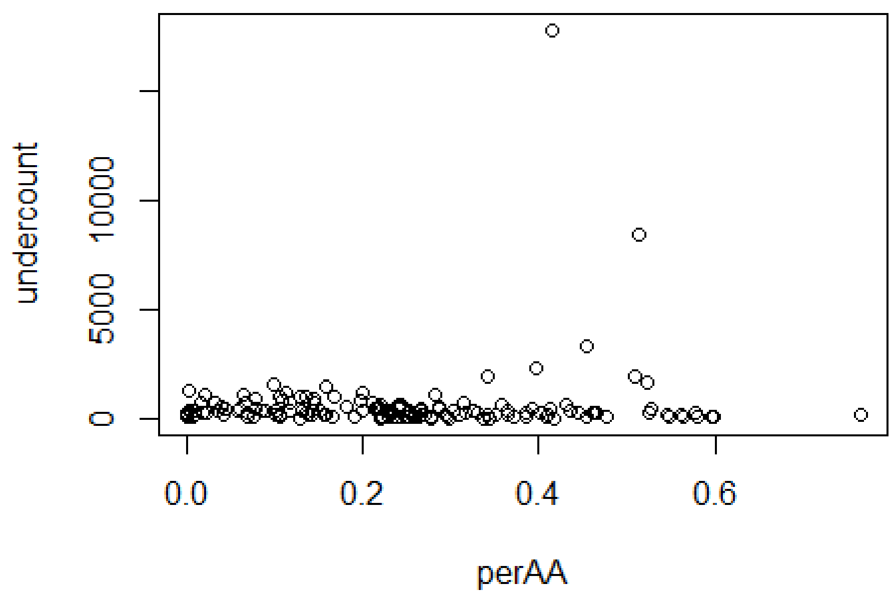


We can also see that the rich use the undercounted equipment much more frequently than the poor people.

```
x2 = xtabs(~equip + poor, data = votes)
p1 = prop.table(x2, margin =1)
p1

##          poor
## equip             0         1
##   LEVER   0.3918919 0.6081081
##   OPTICAL 0.7272727 0.2727273
##   PAPER   0.0000000 1.0000000
##   PUNCH   0.5882353 0.4117647
```

plotting Undercount against Percent AA shows little correlation, but a few large ouliers can be seen in higher AA populations.

```
plot(undercount~perAA, data = votes)
```




```
x = glm(undercount~perAA, data = votes)
summary(x)

##
## Call:
## glm(formula = undercount ~ perAA, data = votes)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1046.2   -482.8   -221.3     21.9  16963.1
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    307.0      225.0   1.365    0.174
## perAA         1187.2      769.5   1.543    0.125
##
## (Dispersion parameter for gaussian family taken to be 2488210)
##
##     Null deviance: 396571504  on 158  degrees of freedom
## Residual deviance: 390648953  on 157  degrees of freedom
## AIC: 2796.8
```

```
##
## Number of Fisher Scoring iterations: 2
```

Conclusion

In conclusion it is not the poor population that is discriminated against but rather the rich population. When looking at the AA population there is very little correlation to undercounting other than a few outliers.

(2)Bootstrapping

Analyze the 5 ETFs

Import the ETFs and view the first 5 rows

```
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

library(fImport)

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

library(foreach)

#Import stocks
stocks = c("SPY", "TLT", "LQD", "EEM", "VNQ")
prices = yahooSeries(stocks, from='2011-01-01', to='2015-08-05')

# The first few rows
head(prices)

## GMT
##            SPY.Open SPY.High SPY.Low SPY.Close SPY.Volume SPY.Adj.Close
## 2011-01-03   126.71   127.60  125.70    127.05  138725200      115.9587
## 2011-01-04   127.33   127.37  126.19    126.98  137409700      115.8948
## 2011-01-05   126.58   127.72  126.46    127.64  133975300      116.4972
## 2011-01-06   127.69   127.83  127.01    127.39  122519000      116.2690
## 2011-01-07   127.56   127.77  126.15    127.14  156034600      116.0409
## 2011-01-10   126.58   127.16  126.20    126.98  122401700      115.8948
##            TLT.Open TLT.High TLT.Low TLT.Close TLT.Volume TLT.Adj.Close
## 2011-01-03    93.20    94.31   92.95     93.41   13799400      81.38658
## 2011-01-04    93.41    93.77   92.91     93.52   10466900      81.48242
## 2011-01-05    92.49    92.69   91.19     91.46   17568000      79.68757
## 2011-01-06    91.54    92.12   91.16     91.86    9317500      80.03609
## 2011-01-07    91.51    92.63   91.03     92.35   12694600      80.46302
## 2011-01-10    92.58    92.99   92.18     92.85    8295200      80.89866
##            LQD.Open LQD.High LQD.Low LQD.Close LQD.Volume LQD.Adj.Close
## 2011-01-03   108.22   108.89  108.06    108.86    2447900      91.64534
## 2011-01-04   108.98   109.19  108.75    109.00     962500      91.76320
## 2011-01-05   108.51   108.58  108.00    108.20    1209200      91.08971
## 2011-01-06   108.32   108.64  108.20    108.36    1089700      91.22441
## 2011-01-07   108.26   109.06  108.20    108.91    1118600      91.68744
## 2011-01-10   108.78   109.20  108.78    109.10     909200      91.84739
##            EEM.Open EEM.High EEM.Low EEM.Close EEM.Volume EEM.Adj.Close
## 2011-01-03    48.03    48.31   48.03     48.10   40116200      43.98749
## 2011-01-04    48.26    48.32   47.75     48.32   45176300      44.18868
## 2011-01-05    47.90    48.30   47.88     48.20   47527100      44.07894
## 2011-01-06    48.01    48.04   47.58     47.69   43977400      43.61254
## 2011-01-07    47.51    47.62   46.93     47.25   57124900      43.21016
## 2011-01-10    46.80    46.85   46.51     46.76   62556500      42.76206
##            VNQ.Open VNQ.High VNQ.Low VNQ.Close VNQ.Volume VNQ.Adj.Close
## 2011-01-03    55.76    56.44   55.73     56.40    1957400      47.62828
## 2011-01-04    56.48    56.63   55.00     55.32    2315700      46.71624
## 2011-01-05    55.15    55.63   55.14     55.52    1512700      46.88514
```

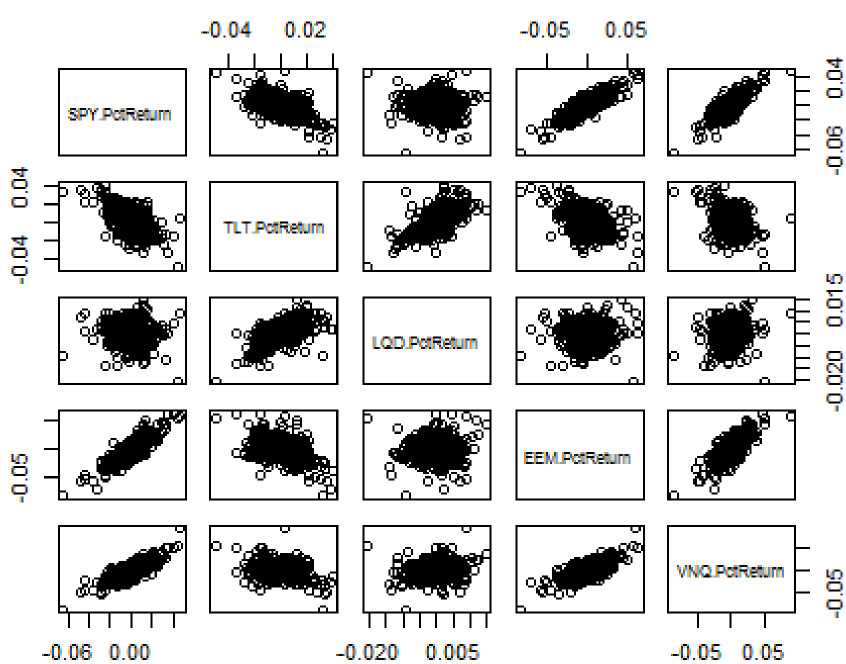
```
## 2011-01-06     55.67     55.68    54.97      55.00     1819300        46.44601
## 2011-01-07     55.29     55.45    54.50      55.02     2001200        46.46290
## 2011-01-10     54.80     55.14    54.42      55.01     1668400        46.45446
```

Creat a function to calculate daily returns of each ETF and then compute the returns

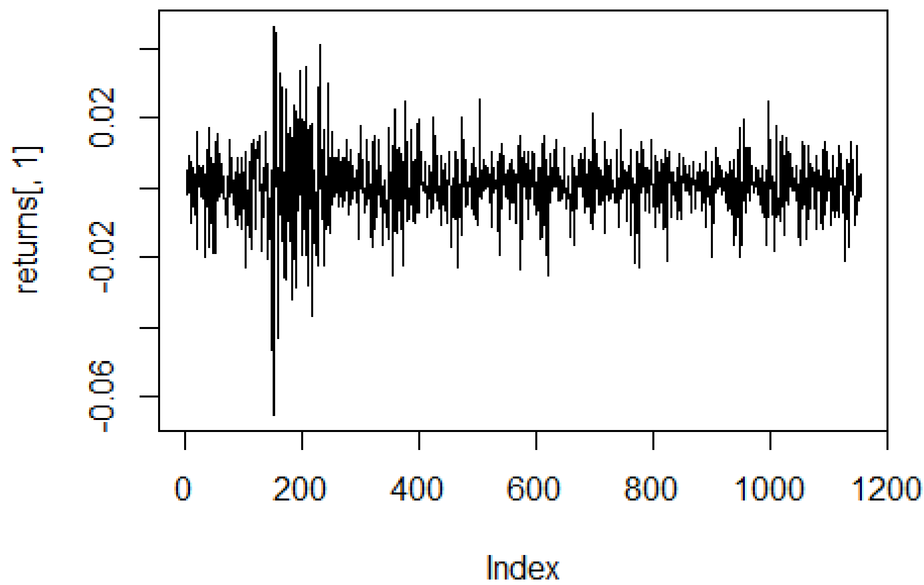
```
YahooPricesToReturns = function(series) {
    mycols = grep('Adj.Close', colnames(series))
    closingprice = series[,mycols]
    N = nrow(closingprice)
    percentreturn = as.data.frame(closingprice[2:N,]) /
as.data.frame(closingprice[1:(N-1),]) - 1
    mynames = strsplit(colnames(percentreturn),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


returns = YahooPricesToReturns(prices)
```

Plot the Returns

```
pairs(returns)
```




```
plot(returns[,1], type='l')
```



Calculate the betas of each stock determined against the market to see which investments are riskier

```
lm_TLT = lm(returns[,2]~returns[,1])
lm_LQD = lm(returns[,3]~returns[,1])
lm_EEM = lm(returns[,4]~returns[,1])
lm_VNQ = lm(returns[,5]~returns[,1])

coef(lm_TLT); coef(lm_LQD); coef(lm_EEM); coef(lm_VNQ)
```

```
##   (Intercept)  returns[, 1]
##  0.0007091476 -0.5626797102

##   (Intercept)  returns[, 1]
##  0.0002286759 -0.0428450593

##   (Intercept)  returns[, 1]
## -0.0007506257  1.2301980660

##   (Intercept)  returns[, 1]
## -0.0000285025  0.9399541016
```

Look at the residuals and their correlations

```
residuals = cbind(resid(lm_TLT), resid(lm_LQD), resid(lm_EEM), resid(lm_VNQ))

cor(residuals)
```

```
##             [,1]      [,2]       [,3]      [,4]
## [1,] 1.00000000 0.7888184 0.03087361 0.2707303
## [2,] 0.78881844 1.0000000 0.17097169 0.3493197
## [3,] 0.03087361 0.1709717 1.00000000 0.1280538
## [4,] 0.27073031 0.3493197 0.12805378 1.0000000
```

Evenly weighted Portfolio:

Set the seed and simulate performance for the safe portfolio. Here the bonds are evenly weighted

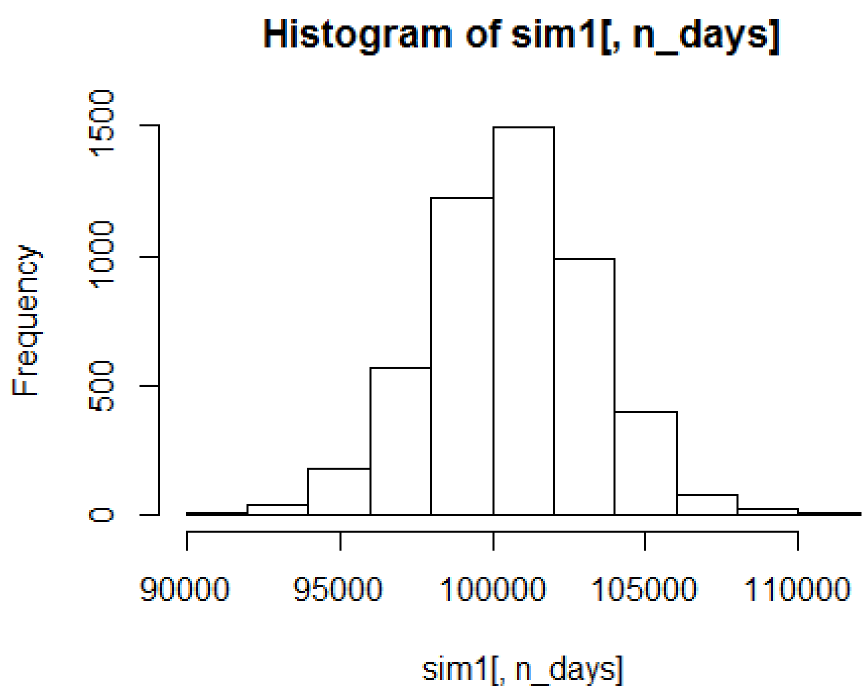
```
n_days=20
set.seed(3000)

sim1 = foreach(i=1:5000, .combine='rbind') %do% {
    totalwealth = 100000
    weights = c(0.2, 0.2, 0.2, 0.2, 0.2)
    holdings = weights * totalwealth
    wealthtracker = rep(0, n_days) # Set up a placeholder to track total
wealth
    for(today in 1:n_days) {
        return.today = resample(returns, 1, orig.ids=FALSE)
        holdings = holdings + holdings*return.today
        totalwealth = sum(holdings)
        holdings = weights * totalwealth
        wealthtracker[today] = totalwealth
    }
    wealthtracker
}
```

Show a selection of Sim1 and plot a histogram of the wealth over 20 days

```
head(sim1)

##               [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## result.1 100842.83 100807.89 100843.17 100762.98 101161.61 100701.92
## result.2 100694.09  99254.37  99456.25  98838.68  99004.05  98161.16
## result.3 100035.54 100094.03 100571.32 100188.06 100506.17 100278.45
## result.4 100507.56 100809.95 100417.39 100931.90 101408.68 101130.46
## result.5 100123.68 100640.27 100986.27 101252.22 100583.03  99696.41
## result.6  99623.42  99608.27 100005.36 100844.86 100615.73  99591.93
##               [,7]      [,8]      [,9]     [,10]     [,11]     [,12]
## result.1 100961.95 100710.30 100564.89 100618.91 100304.57 100498.93
## result.2  98235.78  98357.28  98027.71  97528.78  97982.59  97877.37
## result.3  99826.58  99647.02  99619.48  98939.66  99314.46  99202.39
## result.4 101489.06 101349.91 101979.57 101991.98 102081.31 102119.02
## result.5 100165.18 100250.51  99830.64  99937.80  99201.50  99631.72
## result.6  99992.18 100027.65  99887.70  99536.16  99335.44  99109.74
##              [,13]     [,14]     [,15]     [,16]     [,17]     [,18]
## result.1 100695.81 100127.85  99789.70 100093.82 100470.40 100429.44
## result.2  98457.40  97822.33  97784.23  96980.26  97751.36  98001.20
```

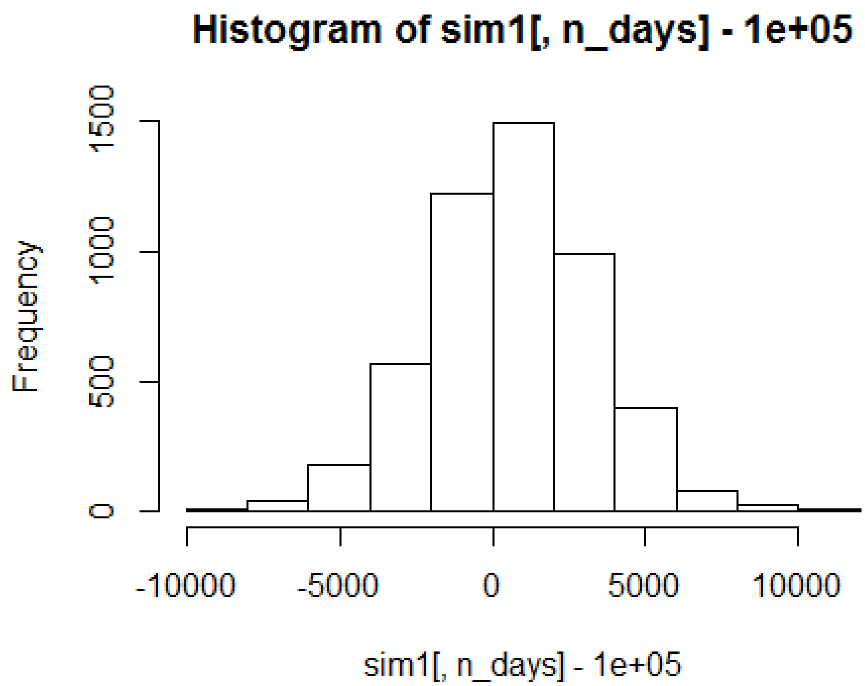
```
## result.3  98964.03  98092.31  98548.75  98521.51  98676.78  98536.17
## result.4 102905.05 102857.38 102746.25 101569.24 101989.80 102049.98
## result.5  99996.01 100433.81 100623.57 100283.38  99274.82  99311.50
## result.6  99487.26  99459.95  99126.93  98768.10  98094.09  97428.78
##              [,19]     [,20]
## result.1  99349.71  99498.96
## result.2  97978.77  97370.37
## result.3  98176.61  98209.07
## result.4 102263.94 102222.25
## result.5 100053.44 100646.38
## result.6  96710.97  97117.65
```

```r
hist(sim1[,n_days])
```



plot a histogram showing profit/loss over the 20 days

```r
hist(sim1[,n_days]- 100000)
```



Calculate 5% value at risk

```
quantile(sim1[,n_days], 0.05) - 100000

##       5% 
## -3869.17
```

Show the average profit or loss

```
mean(sim1[,n_days]- 100000)

## [1] 618.9943
```

Safe Portfolio

Set the seed and simulate performance for the safe portfolio. Here the bonds have been heavily weigted

```
set.seed(4000)

sim2 = foreach(i=1:5000, .combine='rbind') %do% {
    totalwealth = 100000
    weights = c(0.15, 0.3, 0.4, 0.0, 0.15)
    holdings = weights * totalwealth
    wealthtracker = rep(0, n_days) # Set up a placeholder to track total 
wealth
    for(today in 1:n_days) {
        return.today = resample(returns, 1, orig.ids=FALSE)
```

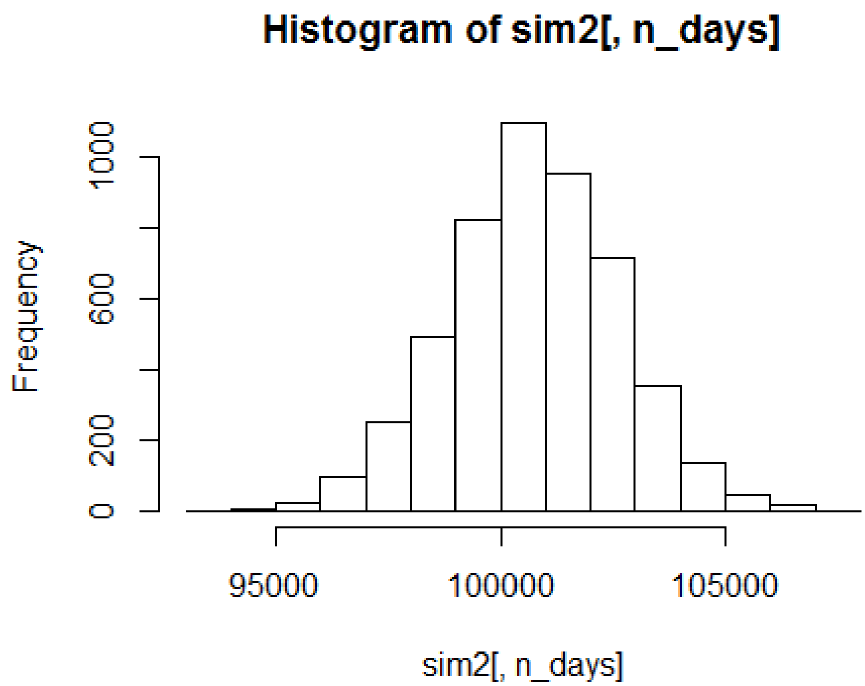
```
        holdings = holdings + holdings*return.today
        totalwealth = sum(holdings)
        holdings = weights * totalwealth
        wealthtracker[today] = totalwealth
    }
    wealthtracker
}
```

Show a selection of Sim2 and plot a histogram of the wealth over 20 days

```
head(sim2)
```

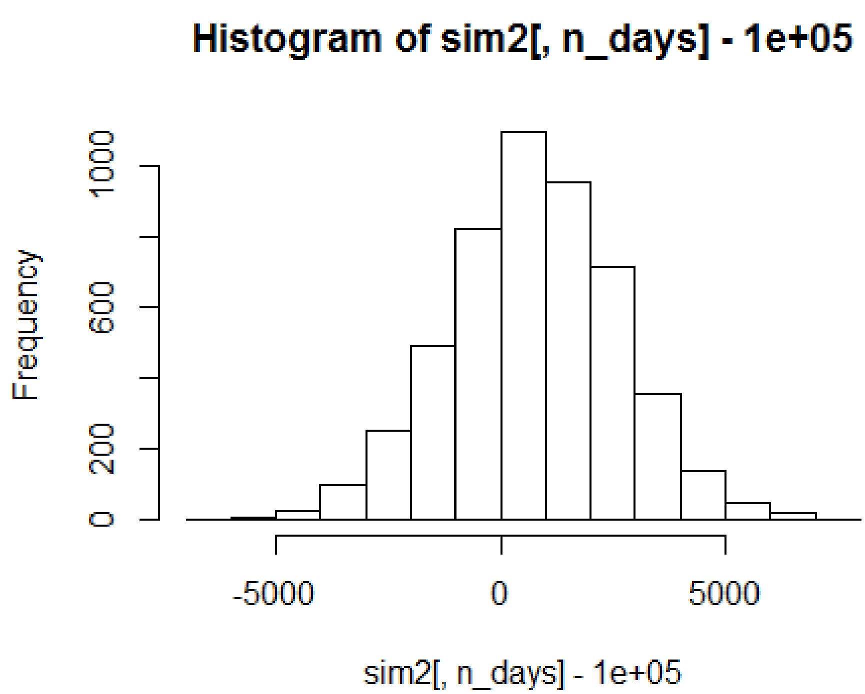
```
##               [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## result.1 100442.76 100730.17 100725.81 101085.10 100708.31 100661.34
## result.2 100737.43 100878.77 101143.97 100827.06 101024.26 100842.55
## result.3  99303.76  99040.03  98752.78  98297.78  98786.38  98816.78
## result.4 100384.21 100565.02 100190.17 100784.47 101342.15 101563.36
## result.5 100162.49 100117.57  99991.39  99684.05  99777.25  99811.77
## result.6 100151.03  99963.78 100400.43 100980.61 100552.75 100840.47
##               [,7]      [,8]      [,9]     [,10]     [,11]     [,12]
## result.1 101005.36 100936.26 100638.48 100826.11 100525.77 100435.80
## result.2 100817.24 100824.81 101162.39 101946.97 101304.65 101364.11
## result.3  98363.90  98512.89  98543.20  98347.81  98216.66  99054.20
## result.4 100923.46 101393.27 101839.20 102330.46 102775.77 103111.03
## result.5  99506.18  99807.34  99816.33  99373.98  99507.36  99782.32
## result.6 101073.80 101209.46 101326.76 101540.99 101206.85 101230.32
##              [,13]     [,14]     [,15]     [,16]     [,17]     [,18]
## result.1 100632.23 100105.05 100382.90 100388.20 100582.88 101301.50
## result.2 102153.95 102478.92 103193.41 102976.79 102800.60 103031.71
## result.3  98155.65  98306.50  98279.83  97618.74  97730.57  97730.30
## result.4 103216.85 103022.95 103296.97 103433.82 103666.35 103692.58
## result.5  99396.68  99030.88  98884.85  97979.98  97706.00  97779.11
## result.6 101936.11 101457.89 101356.30 101675.97 101401.39 101550.43
##              [,19]     [,20]
## result.1 101048.14 100433.33
## result.2 103018.87 103373.32
## result.3  97874.27  98030.42
## result.4 103944.47 104100.60
## result.5  97910.35  97957.72
## result.6 102043.03 102749.30
```

```
hist(sim2[,n_days])
```



plot a histogram showing profit/loss over the 20 days

```
hist(sim2[,n_days]- 100000)
```



Calculate 5% value at risk

```
quantile(sim2[,n_days], 0.05) - 100000

##        5%
## -2417.244
```

Show the average profit or loss

```
#Average Profit/Loss
mean(sim2[,n_days]- 100000)

## [1] 734.0009
```

Risky Portfolio

Set the seed and simulate performance for the risky portfolio. Here the bonds have been excluded

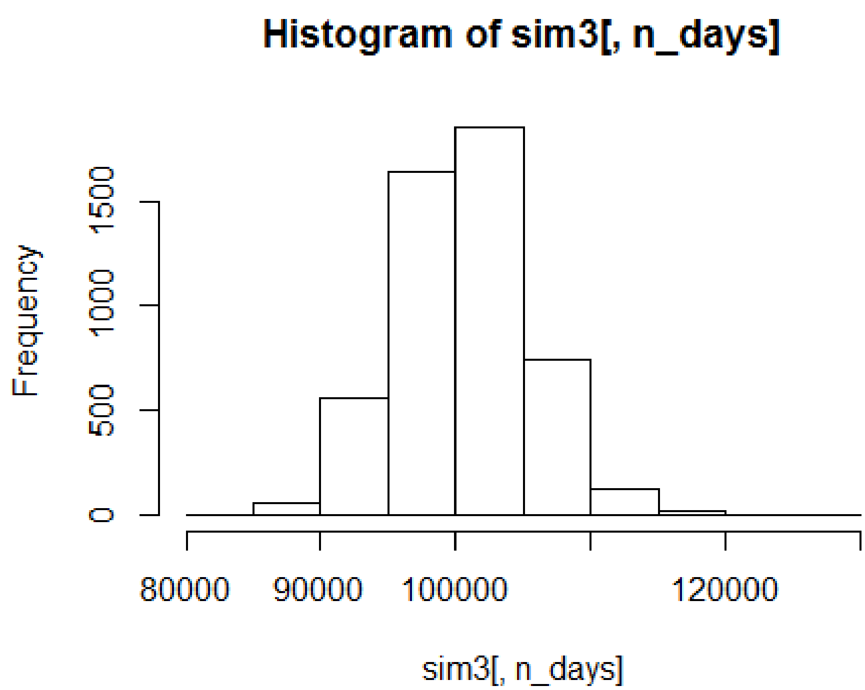
```
set.seed(2000)

sim3 = foreach(i=1:5000, .combine='rbind') %do% {
    totalwealth = 100000
    weights = c(0.4, 0.0, 0.0, 0.4, 0.2)
    holdings = weights * totalwealth
    wealthtracker = rep(0, n_days) # Set up a placeholder to track total
wealth
    for(today in 1:n_days) {
        return.today = resample(returns, 1, orig.ids=FALSE)
        holdings = holdings + holdings*return.today
        totalwealth = sum(holdings)
        holdings = weights * totalwealth
        wealthtracker[today] = totalwealth
    }
    wealthtracker
}
```

Show a selection of Sim3 and plot a histogram of the wealth over 20 days

```
head(sim3)

##               [,1]     [,2]     [,3]      [,4]     [,5]      [,6]
## result.1  99880.23 100184.5 100017.2 100458.52 101228.9 100881.73
## result.2 101058.13 101232.2 101793.4 101916.34 102147.7 102571.41
## result.3  99817.85 100037.2 100036.0 101475.47 101232.1 100535.13
## result.4 103068.40 101579.9 102820.5 101010.85 100117.7  99469.64
## result.5 101240.73 101678.6  99453.0  99973.87  97625.2  97651.87
## result.6 100941.02 100487.9 100083.9  99786.64 101138.2 101015.01
##               [,7]      [,8]      [,9]     [,10]     [,11]     [,12]
## result.1 100010.42  99775.03 101503.20 101546.61 101648.38 104827.07
## result.2 102658.24 102779.24 101071.49 100270.67  99159.27 101093.51
## result.3 100445.79  99933.25  98876.02  99418.32  99118.70  98061.48
```

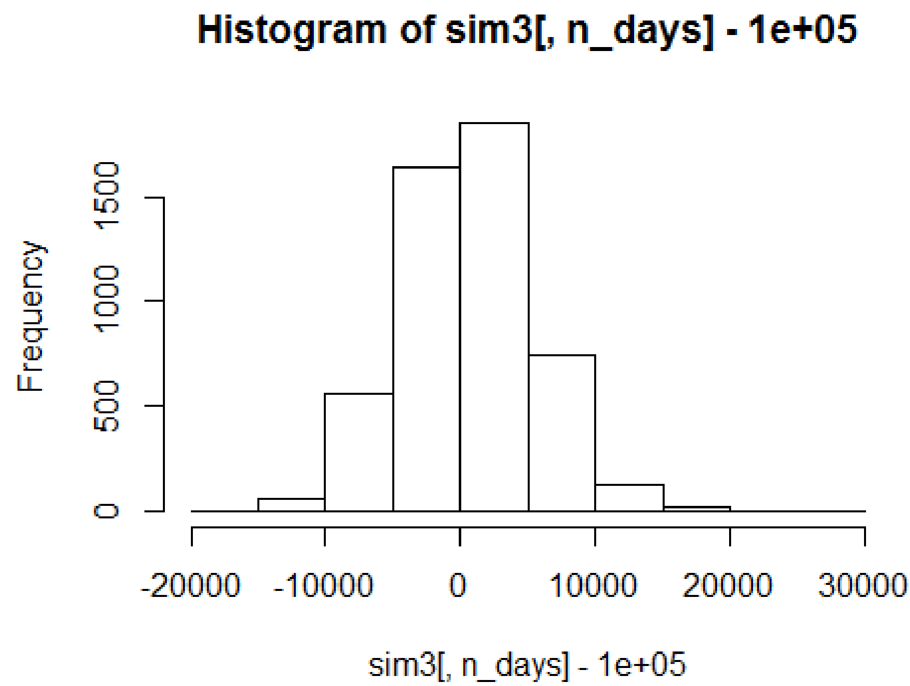
```
## result.4  99967.10 101444.45 102918.13 103670.91 102957.16 102449.68
## result.5  97830.44  97608.02  97571.06  97395.53  98389.70  97996.39
## result.6 105837.69 104193.51 104422.44 104478.70 103075.06 104287.14
##              [,13]     [,14]     [,15]     [,16]     [,17]     [,18]
## result.1 105488.89 104689.64 102435.51 102386.41 102468.40 103490.39
## result.2 101123.72 101465.81 100815.20 101227.69 101257.94 102329.38
## result.3  96881.90  97980.65  98390.16  99041.60  99709.57 100147.67
## result.4 102199.06 102093.22 102870.53 104506.71 104739.68 104145.47
## result.5  98593.56  98828.27  97126.38  98523.94  99362.55  99971.82
## result.6 104206.42 104989.69 103667.83 104575.87 105483.84 105498.81
##              [,19]     [,20]
## result.1 104561.39 105785.17
## result.2 102420.84 101334.10
## result.3  99854.57 101031.83
## result.4 104000.14 104853.38
## result.5  98516.27  99574.83
## result.6 106494.24 105646.79
```

```r
hist(sim3[,n_days])
```



plot a histogram showing profit/loss over the 20 days

```r
hist(sim3[,n_days]- 100000)
```



Calculate 5% value at risk

```
quantile(sim3[,n_days], 0.05) - 100000

##        5%
## -7258.986
```

Show the average profit or loss

```
mean(sim3[,n_days]- 100000)

## [1] 593.1402
```

Conclusion

Ultimately the safe portfolio had the best average return and the least amount at stake. The risky portfoli had the worst return and the most money at stake.

(3)Clustering And PCA

Red Vs White Clustering

Read in the data

```r
wine = read.csv('wine.csv')

head(wine)
```

```
##   fixed.acidity volatile.acidity citric.acid residual.sugar chlorides
## 1           7.4             0.70        0.00            1.9     0.076
## 2           7.8             0.88        0.00            2.6     0.098
## 3           7.8             0.76        0.04            2.3     0.092
## 4          11.2             0.28        0.56            1.9     0.075
## 5           7.4             0.70        0.00            1.9     0.076
## 6           7.4             0.66        0.00            1.8     0.075
##   free.sulfur.dioxide total.sulfur.dioxide density   pH sulphates alcohol
## 1                  11                   34  0.9978 3.51      0.56     9.4
## 2                  25                   67  0.9968 3.20      0.68     9.8
## 3                  15                   54  0.9970 3.26      0.65     9.8
## 4                  17                   60  0.9980 3.16      0.58     9.8
## 5                  11                   34  0.9978 3.51      0.56     9.4
## 6                  13                   40  0.9978 3.51      0.56     9.4
##   quality color
## 1       5   red
## 2       5   red
## 3       5   red
## 4       6   red
## 5       5   red
## 6       5   red
```

```r
names(wine)
```

```
##  [1] "fixed.acidity"        "volatile.acidity"     "citric.acid"
##  [4] "residual.sugar"       "chlorides"            "free.sulfur.dioxide"
##  [7] "total.sulfur.dioxide" "density"              "pH"
## [10] "sulphates"            "alcohol"              "quality"
## [13] "color"
```

Remove the last 2 columns and scale the data.

```r
wine_num = wine [,(1:11)]
wine_scaled = scale(wine_num, center = TRUE, scale = TRUE)
```

cluster the data using 2 centers, in hopes of distinguishing red from white wine.

```r
cluster_2 = kmeans(wine_scaled, centers = 2, nstart = 50)
```

Capture the mean and SD of the scaled data.

```r
sigma = attr(wine_scaled,"scaled:scale")
mu = attr(wine_scaled,"scaled:center")
```

Unscale the data.

```r
cluster_2$center
```

```
##   fixed.acidity volatile.acidity citric.acid residual.sugar  chlorides
## 1    -0.2804833       -0.3953082   0.1143429      0.1998380 -0.3119753
## 2     0.8286464        1.1678795  -0.3378091     -0.5903919  0.9216848
##   free.sulfur.dioxide total.sulfur.dioxide    density         pH
## 1           0.2814861            0.4018607 -0.2306934 -0.1920315
## 2          -0.8316090           -1.1872380  0.6815493  0.5673286
##    sulphates     alcohol
## 1 -0.2853595  0.02562065
## 2  0.8430523 -0.07569241
```

```
cluster_2$center[1,]*sigma + mu
```

```
##        fixed.acidity     volatile.acidity          citric.acid
##           6.85167903           0.27458385           0.33524928
##       residual.sugar            chlorides  free.sulfur.dioxide
##           6.39402555           0.04510424          35.52152864
## total.sulfur.dioxide              density                   pH
##         138.45848785           0.99400486           3.18762464
##            sulphates              alcohol
##           0.48880511          10.52235888
```

```
cluster_2$center[2,]*sigma + mu
```

```
##        fixed.acidity     volatile.acidity          citric.acid
##            8.2895922            0.5319416            0.2695435
##       residual.sugar            chlorides  free.sulfur.dioxide
##            2.6342666            0.0883238           15.7647596
## total.sulfur.dioxide              density                   pH
##           48.6396835            0.9967404            3.3097200
##            sulphates              alcohol
##            0.6567194           10.4015216
```

See which wines are in each cluster

```
which(cluster_2$cluster == 1)
```

```
##    [1]   50  355  495  592  635  650  837  838 1018 1019 1080 1082 1091
##   [14] 1115 1132 1157 1236 1245 1287 1390 1457 1491 1567 1575 1600 1601
##   [27] 1602 1603 1604 1605 1606 1607 1608 1609 1610 1611 1612 1613 1614
##   [40] 1615 1616 1617 1618 1619 1620 1621 1622 1623 1624 1625 1626 1627
##   [53] 1628 1629 1630 1631 1632 1633 1634 1635 1636 1637 1638 1639 1640
##   [66] 1641 1642 1643 1644 1645 1646 1647 1648 1649 1650 1651 1652 1653
##   [79] 1654 1655 1656 1657 1658 1659 1660 1661 1662 1663 1664 1665 1666
##   [92] 1667 1668 1669 1670 1671 1672 1673 1674 1675 1676 1677 1678 1679
##  [105] 1680 1681 1682 1683 1684 1685 1686 1687 1688 1689 1690 1691 1692
##  [118] 1693 1694 1695 1696 1697 1698 1699 1700 1701 1702 1703 1704 1705
##  [131] 1706 1707 1708 1709 1710 1711 1712 1713 1714 1716 1717 1718 1719
##  [144] 1720 1721 1722 1723 1724 1725 1726 1727 1728 1729 1730 1731 1732
##  [157] 1733 1734 1735 1736 1737 1738 1739 1740 1741 1742 1743 1744 1745
##  [170] 1746 1748 1749 1750 1751 1752 1753 1755 1756 1757 1758 1759 1760
##  [183] 1761 1762 1763 1764 1765 1766 1767 1768 1769 1770 1771 1772 1773
##  [196] 1774 1775 1776 1777 1778 1779 1780 1781 1782 1783 1784 1785 1786
```

```
##  [209] 1787 1788 1789 1790 1791 1792 1793 1794 1795 1796 1797 1798 1799
##  [222] 1800 1801 1802 1803 1804 1805 1806 1807 1809 1810 1811 1812 1813
##  [235] 1814 1815 1816 1817 1818 1819 1820 1821 1822 1823 1824 1825 1826
##  [248] 1827 1828 1829 1831 1832 1833 1834 1835 1836 1837 1838 1839 1840
##  [261] 1841 1842 1843 1844 1845 1846 1847 1848 1849 1850 1851 1852 1853
##  [274] 1854 1855 1856 1857 1858 1859 1860 1861 1862 1863 1864 1865 1866
##  [287] 1867 1868 1869 1870 1871 1872 1873 1874 1875 1876 1877 1878 1879
##  [300] 1880 1881 1882 1883 1884 1885 1886 1887 1888 1889 1890 1891 1892
##  [313] 1893 1894 1895 1896 1897 1898 1899 1900 1901 1902 1903 1904 1905
##  [326] 1906 1907 1908 1909 1910 1911 1912 1913 1914 1915 1916 1917 1918
##  [339] 1919 1920 1921 1922 1923 1924 1925 1926 1927 1928 1929 1930 1931
##  [352] 1932 1933 1934 1935 1936 1937 1938 1939 1940 1941 1942 1943 1944
##  [365] 1945 1946 1947 1948 1949 1950 1951 1952 1953 1954 1955 1956 1957
##  [378] 1958 1959 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970
##  [391] 1971 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984
##  [404] 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997
##  [417] 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010
##  [430] 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023
##  [443] 2024 2025 2026 2027 2028 2029 2030 2031 2032 2034 2035 2036 2037
##  [456] 2038 2039 2040 2041 2042 2043 2044 2045 2046 2047 2048 2049 2050
##  [469] 2051 2052 2053 2054 2055 2056 2057 2058 2059 2060 2061 2062 2063
##  [482] 2064 2065 2066 2067 2068 2069 2070 2071 2072 2073 2074 2075 2076
##  [495] 2077 2078 2079 2080 2081 2082 2083 2085 2086 2087 2088 2089 2090
##  [508] 2091 2092 2093 2094 2095 2096 2097 2098 2099 2100 2101 2102 2103
##  [521] 2104 2105 2107 2108 2109 2110 2111 2112 2113 2114 2115 2116 2117
##  [534] 2118 2119 2120 2121 2122 2123 2124 2125 2126 2127 2128 2129 2130
##  [547] 2131 2132 2133 2134 2135 2136 2137 2138 2139 2140 2141 2142 2143
##  [560] 2144 2145 2146 2147 2148 2149 2150 2151 2152 2153 2154 2155 2156
##  [573] 2157 2158 2159 2160 2161 2162 2163 2164 2165 2166 2167 2168 2169
##  [586] 2170 2171 2172 2173 2174 2175 2176 2177 2178 2179 2180 2181 2182
##  [599] 2183 2184 2185 2186 2187 2188 2189 2190 2191 2192 2193 2194 2195
##  [612] 2196 2197 2198 2199 2200 2201 2202 2203 2204 2205 2206 2207 2208
##  [625] 2210 2211 2212 2213 2214 2215 2216 2217 2218 2219 2220 2221 2222
##  [638] 2223 2224 2225 2227 2228 2229 2230 2231 2232 2233 2234 2235 2236
##  [651] 2237 2238 2239 2240 2241 2242 2243 2244 2245 2246 2247 2248 2249
##  [664] 2250 2251 2252 2253 2254 2255 2256 2257 2258 2259 2260 2261 2263
##  [677] 2264 2265 2266 2267 2268 2269 2270 2271 2272 2273 2274 2275 2276
##  [690] 2277 2278 2279 2280 2281 2282 2283 2284 2285 2286 2288 2289 2290
##  [703] 2291 2292 2293 2294 2295 2296 2297 2298 2299 2300 2301 2302 2303
##  [716] 2304 2305 2306 2307 2308 2309 2310 2311 2312 2313 2314 2315 2316
##  [729] 2317 2318 2319 2320 2321 2322 2323 2324 2325 2326 2327 2328 2329
##  [742] 2330 2331 2332 2333 2334 2335 2336 2337 2338 2339 2340 2341 2342
##  [755] 2343 2344 2345 2346 2347 2348 2349 2350 2351 2352 2353 2354 2355
##  [768] 2356 2357 2358 2359 2360 2361 2362 2363 2364 2365 2366 2367 2368
##  [781] 2369 2370 2371 2372 2373 2374 2375 2376 2377 2378 2379 2380 2381
##  [794] 2382 2383 2384 2385 2386 2387 2388 2389 2390 2391 2392 2393 2394
##  [807] 2395 2396 2397 2398 2399 2400 2401 2402 2403 2404 2405 2406 2407
##  [820] 2408 2409 2410 2411 2412 2413 2414 2415 2416 2417 2418 2419 2420
##  [833] 2421 2422 2423 2424 2425 2426 2427 2428 2429 2431 2432 2433 2435
##  [846] 2436 2437 2438 2439 2440 2441 2442 2443 2444 2445 2446 2447 2448
```

```
##  [859] 2449 2450 2451 2452 2453 2454 2455 2456 2457 2458 2459 2460 2461
##  [872] 2462 2463 2464 2465 2466 2467 2468 2469 2470 2471 2472 2473 2474
##  [885] 2475 2476 2477 2478 2479 2480 2481 2482 2483 2484 2485 2486 2487
##  [898] 2488 2489 2490 2491 2492 2493 2494 2495 2496 2497 2498 2499 2500
##  [911] 2501 2502 2503 2504 2505 2506 2507 2508 2509 2510 2511 2512 2513
##  [924] 2514 2515 2516 2517 2518 2519 2520 2521 2522 2523 2524 2525 2526
##  [937] 2527 2528 2529 2530 2531 2532 2533 2534 2535 2536 2537 2538 2539
##  [950] 2540 2541 2542 2543 2544 2545 2546 2547 2549 2550 2551 2552 2553
##  [963] 2554 2555 2556 2557 2558 2559 2560 2561 2562 2563 2564 2565 2566
##  [976] 2567 2568 2569 2570 2571 2572 2573 2574 2575 2576 2577 2578 2579
##  [989] 2580 2581 2582 2583 2584 2585 2586 2587 2588 2589 2590 2591 2592
## [1002] 2593 2594 2595 2596 2597 2598 2599 2600 2601 2602 2603 2604 2605
## [1015] 2606 2607 2608 2609 2610 2611 2612 2613 2614 2615 2616 2617 2618
## [1028] 2619 2620 2621 2622 2623 2624 2625 2626 2627 2628 2629 2630 2631
## [1041] 2632 2633 2635 2638 2639 2641 2642 2643 2644 2645 2646 2647 2648
## [1054] 2649 2650 2651 2652 2653 2654 2655 2656 2657 2658 2659 2660 2661
## [1067] 2662 2663 2664 2665 2666 2667 2668 2669 2670 2671 2672 2673 2674
## [1080] 2675 2676 2677 2678 2679 2680 2681 2682 2683 2684 2685 2686 2687
## [1093] 2688 2689 2690 2691 2692 2693 2694 2695 2696 2697 2698 2699 2700
## [1106] 2701 2702 2703 2704 2705 2706 2707 2708 2709 2710 2711 2712 2713
## [1119] 2715 2716 2717 2718 2719 2720 2721 2722 2723 2724 2725 2726 2727
## [1132] 2728 2729 2730 2731 2732 2733 2734 2735 2736 2737 2738 2739 2740
## [1145] 2741 2742 2743 2744 2745 2746 2747 2748 2749 2750 2751 2753 2754
## [1158] 2755 2756 2757 2758 2759 2760 2761 2762 2763 2764 2765 2766 2767
## [1171] 2768 2769 2770 2771 2772 2773 2774 2775 2776 2777 2778 2779 2780
## [1184] 2781 2782 2783 2784 2785 2786 2787 2788 2789 2790 2791 2792 2793
## [1197] 2794 2795 2796 2797 2798 2799 2800 2801 2802 2803 2804 2805 2806
## [1210] 2807 2808 2809 2810 2811 2812 2813 2814 2815 2816 2818 2819 2820
## [1223] 2821 2822 2823 2824 2825 2826 2827 2828 2829 2830 2831 2832 2833
## [1236] 2834 2835 2836 2837 2838 2839 2840 2841 2842 2843 2844 2845 2846
## [1249] 2847 2848 2849 2850 2851 2852 2853 2854 2855 2856 2857 2858 2859
## [1262] 2860 2861 2862 2863 2864 2865 2866 2867 2868 2869 2870 2871 2873
## [1275] 2874 2875 2876 2877 2878 2879 2880 2881 2882 2883 2884 2885 2886
## [1288] 2887 2888 2889 2890 2891 2892 2893 2894 2895 2896 2897 2898 2899
## [1301] 2900 2901 2902 2903 2904 2905 2906 2907 2908 2909 2910 2911 2912
## [1314] 2913 2914 2915 2916 2917 2918 2919 2920 2921 2922 2923 2924 2925
## [1327] 2926 2927 2928 2929 2930 2931 2932 2933 2934 2935 2936 2937 2938
## [1340] 2939 2940 2941 2942 2943 2944 2945 2946 2947 2948 2949 2950 2951
## [1353] 2952 2953 2954 2955 2956 2957 2958 2959 2960 2961 2962 2963 2964
## [1366] 2965 2966 2967 2968 2969 2970 2971 2972 2973 2974 2975 2976 2977
## [1379] 2978 2979 2980 2981 2982 2983 2984 2985 2987 2988 2989 2990 2991
## [1392] 2992 2993 2995 2996 2997 2998 2999 3000 3001 3002 3003 3004 3005
## [1405] 3006 3007 3008 3009 3010 3011 3012 3013 3014 3015 3016 3017 3018
## [1418] 3019 3020 3021 3022 3023 3024 3025 3026 3027 3028 3029 3030 3031
## [1431] 3032 3033 3034 3035 3036 3037 3038 3039 3040 3041 3042 3043 3044
## [1444] 3045 3046 3047 3048 3049 3050 3051 3052 3053 3054 3055 3056 3057
## [1457] 3058 3059 3060 3061 3062 3063 3064 3065 3066 3067 3068 3069 3070
## [1470] 3071 3072 3073 3074 3075 3076 3077 3078 3079 3080 3081 3082 3083
## [1483] 3084 3085 3086 3087 3088 3089 3090 3091 3092 3093 3094 3095 3097
## [1496] 3098 3099 3100 3101 3102 3103 3104 3105 3106 3107 3108 3109 3110
```

```
## [1509] 3111 3112 3113 3114 3115 3116 3117 3118 3119 3120 3121 3122 3123
## [1522] 3124 3125 3126 3127 3128 3129 3130 3131 3132 3133 3134 3135 3136
## [1535] 3137 3138 3139 3140 3141 3142 3143 3144 3145 3146 3147 3148 3149
## [1548] 3150 3151 3152 3153 3154 3155 3156 3157 3158 3159 3160 3161 3162
## [1561] 3163 3164 3165 3166 3167 3168 3169 3170 3171 3172 3173 3174 3175
## [1574] 3176 3178 3179 3180 3181 3182 3183 3184 3185 3186 3187 3188 3189
## [1587] 3190 3191 3192 3193 3194 3195 3196 3197 3198 3199 3200 3201 3202
## [1600] 3203 3204 3205 3206 3207 3208 3209 3210 3211 3212 3213 3214 3215
## [1613] 3216 3217 3218 3219 3220 3221 3222 3223 3224 3225 3226 3227 3228
## [1626] 3229 3230 3231 3232 3233 3234 3235 3236 3237 3238 3239 3240 3241
## [1639] 3242 3243 3244 3245 3246 3247 3248 3249 3250 3251 3252 3253 3254
## [1652] 3255 3256 3257 3258 3259 3260 3261 3262 3263 3264 3265 3266 3267
## [1665] 3268 3269 3270 3271 3272 3273 3274 3275 3276 3277 3278 3279 3280
## [1678] 3281 3282 3283 3284 3285 3286 3287 3288 3289 3290 3291 3292 3293
## [1691] 3294 3295 3296 3297 3298 3299 3300 3301 3302 3303 3304 3305 3306
## [1704] 3307 3309 3310 3311 3312 3313 3314 3315 3316 3317 3318 3319 3320
## [1717] 3321 3322 3323 3324 3325 3326 3327 3328 3329 3330 3331 3332 3333
## [1730] 3334 3335 3336 3337 3338 3339 3340 3341 3342 3343 3344 3345 3346
## [1743] 3347 3348 3349 3350 3351 3352 3353 3354 3355 3356 3357 3358 3359
## [1756] 3360 3361 3362 3363 3364 3365 3366 3367 3368 3369 3370 3371 3372
## [1769] 3373 3374 3375 3376 3377 3378 3379 3380 3381 3382 3384 3385 3386
## [1782] 3387 3388 3389 3390 3391 3392 3393 3394 3395 3396 3397 3398 3399
## [1795] 3400 3401 3402 3403 3404 3405 3406 3407 3408 3409 3410 3411 3412
## [1808] 3413 3414 3415 3416 3417 3418 3419 3420 3421 3422 3423 3424 3425
## [1821] 3426 3427 3428 3429 3430 3431 3432 3433 3434 3436 3437 3438 3439
## [1834] 3440 3441 3442 3443 3444 3445 3446 3447 3448 3449 3450 3451 3452
## [1847] 3453 3454 3455 3457 3458 3459 3460 3461 3462 3463 3464 3466 3467
## [1860] 3468 3469 3470 3471 3472 3473 3474 3475 3476 3477 3478 3479 3480
## [1873] 3481 3482 3483 3484 3485 3486 3487 3488 3489 3490 3491 3492 3493
## [1886] 3494 3495 3496 3497 3498 3499 3500 3501 3502 3503 3504 3505 3506
## [1899] 3507 3508 3509 3510 3511 3512 3513 3514 3515 3516 3517 3518 3519
## [1912] 3520 3521 3522 3523 3524 3525 3527 3528 3529 3530 3531 3533 3534
## [1925] 3535 3536 3537 3538 3539 3540 3541 3542 3543 3544 3545 3546 3547
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##  [261]  262  263  264  265  266  267  268  269  270  271  272  273  274
##  [274]  275  276  277  278  279  280  281  282  283  284  285  286  287
##  [287]  288  289  290  291  292  293  294  295  296  297  298  299  300
##  [300]  301  302  303  304  305  306  307  308  309  310  311  312  313
##  [313]  314  315  316  317  318  319  320  321  322  323  324  325  326
##  [326]  327  328  329  330  331  332  333  334  335  336  337  338  339
##  [339]  340  341  342  343  344  345  346  347  348  349  350  351  352
##  [352]  353  354  356  357  358  359  360  361  362  363  364  365  366
##  [365]  367  368  369  370  371  372  373  374  375  376  377  378  379
##  [378]  380  381  382  383  384  385  386  387  388  389  390  391  392
##  [391]  393  394  395  396  397  398  399  400  401  402  403  404  405
##  [404]  406  407  408  409  410  411  412  413  414  415  416  417  418
##  [417]  419  420  421  422  423  424  425  426  427  428  429  430  431
##  [430]  432  433  434  435  436  437  438  439  440  441  442  443  444
##  [443]  445  446  447  448  449  450  451  452  453  454  455  456  457
##  [456]  458  459  460  461  462  463  464  465  466  467  468  469  470
##  [469]  471  472  473  474  475  476  477  478  479  480  481  482  483
##  [482]  484  485  486  487  488  489  490  491  492  493  494  496  497
##  [495]  498  499  500  501  502  503  504  505  506  507  508  509  510
```
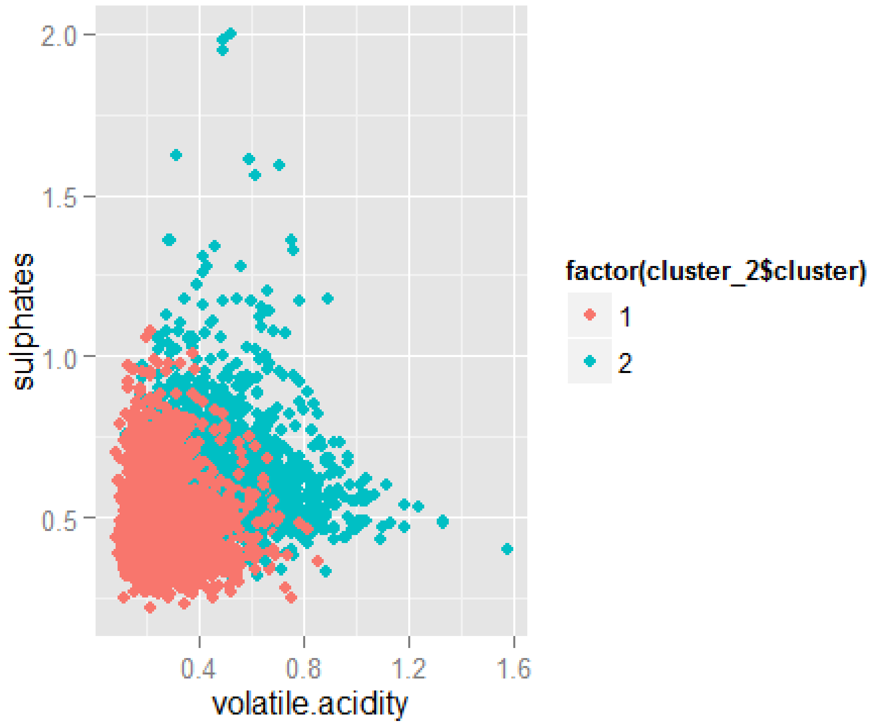

```
##  [508]  511  512  513  514  515  516  517  518  519  520  521  522  523
##  [521]  524  525  526  527  528  529  530  531  532  533  534  535  536
##  [534]  537  538  539  540  541  542  543  544  545  546  547  548  549
##  [547]  550  551  552  553  554  555  556  557  558  559  560  561  562
##  [560]  563  564  565  566  567  568  569  570  571  572  573  574  575
##  [573]  576  577  578  579  580  581  582  583  584  585  586  587  588
##  [586]  589  590  591  593  594  595  596  597  598  599  600  601  602
##  [599]  603  604  605  606  607  608  609  610  611  612  613  614  615
##  [612]  616  617  618  619  620  621  622  623  624  625  626  627  628
##  [625]  629  630  631  632  633  634  636  637  638  639  640  641  642
##  [638]  643  644  645  646  647  648  649  651  652  653  654  655  656
##  [651]  657  658  659  660  661  662  663  664  665  666  667  668  669
##  [664]  670  671  672  673  674  675  676  677  678  679  680  681  682
##  [677]  683  684  685  686  687  688  689  690  691  692  693  694  695
##  [690]  696  697  698  699  700  701  702  703  704  705  706  707  708
##  [703]  709  710  711  712  713  714  715  716  717  718  719  720  721
##  [716]  722  723  724  725  726  727  728  729  730  731  732  733  734
##  [729]  735  736  737  738  739  740  741  742  743  744  745  746  747
##  [742]  748  749  750  751  752  753  754  755  756  757  758  759  760
##  [755]  761  762  763  764  765  766  767  768  769  770  771  772  773
##  [768]  774  775  776  777  778  779  780  781  782  783  784  785  786
##  [781]  787  788  789  790  791  792  793  794  795  796  797  798  799
##  [794]  800  801  802  803  804  805  806  807  808  809  810  811  812
##  [807]  813  814  815  816  817  818  819  820  821  822  823  824  825
##  [820]  826  827  828  829  830  831  832  833  834  835  836  839  840
##  [833]  841  842  843  844  845  846  847  848  849  850  851  852  853
##  [846]  854  855  856  857  858  859  860  861  862  863  864  865  866
##  [859]  867  868  869  870  871  872  873  874  875  876  877  878  879
##  [872]  880  881  882  883  884  885  886  887  888  889  890  891  892
##  [885]  893  894  895  896  897  898  899  900  901  902  903  904  905
##  [898]  906  907  908  909  910  911  912  913  914  915  916  917  918
##  [911]  919  920  921  922  923  924  925  926  927  928  929  930  931
##  [924]  932  933  934  935  936  937  938  939  940  941  942  943  944
##  [937]  945  946  947  948  949  950  951  952  953  954  955  956  957
##  [950]  958  959  960  961  962  963  964  965  966  967  968  969  970
##  [963]  971  972  973  974  975  976  977  978  979  980  981  982  983
##  [976]  984  985  986  987  988  989  990  991  992  993  994  995  996
##  [989]  997  998  999 1000 1001 1002 1003 1004 1005 1006 1007 1008 1009
## [1002] 1010 1011 1012 1013 1014 1015 1016 1017 1020 1021 1022 1023 1024
## [1015] 1025 1026 1027 1028 1029 1030 1031 1032 1033 1034 1035 1036 1037
## [1028] 1038 1039 1040 1041 1042 1043 1044 1045 1046 1047 1048 1049 1050
## [1041] 1051 1052 1053 1054 1055 1056 1057 1058 1059 1060 1061 1062 1063
## [1054] 1064 1065 1066 1067 1068 1069 1070 1071 1072 1073 1074 1075 1076
## [1067] 1077 1078 1079 1081 1083 1084 1085 1086 1087 1088 1089 1090 1092
## [1080] 1093 1094 1095 1096 1097 1098 1099 1100 1101 1102 1103 1104 1105
## [1093] 1106 1107 1108 1109 1110 1111 1112 1113 1114 1116 1117 1118 1119
## [1106] 1120 1121 1122 1123 1124 1125 1126 1127 1128 1129 1130 1131 1133
## [1119] 1134 1135 1136 1137 1138 1139 1140 1141 1142 1143 1144 1145 1146
## [1132] 1147 1148 1149 1150 1151 1152 1153 1154 1155 1156 1158 1159 1160
## [1145] 1161 1162 1163 1164 1165 1166 1167 1168 1169 1170 1171 1172 1173
```

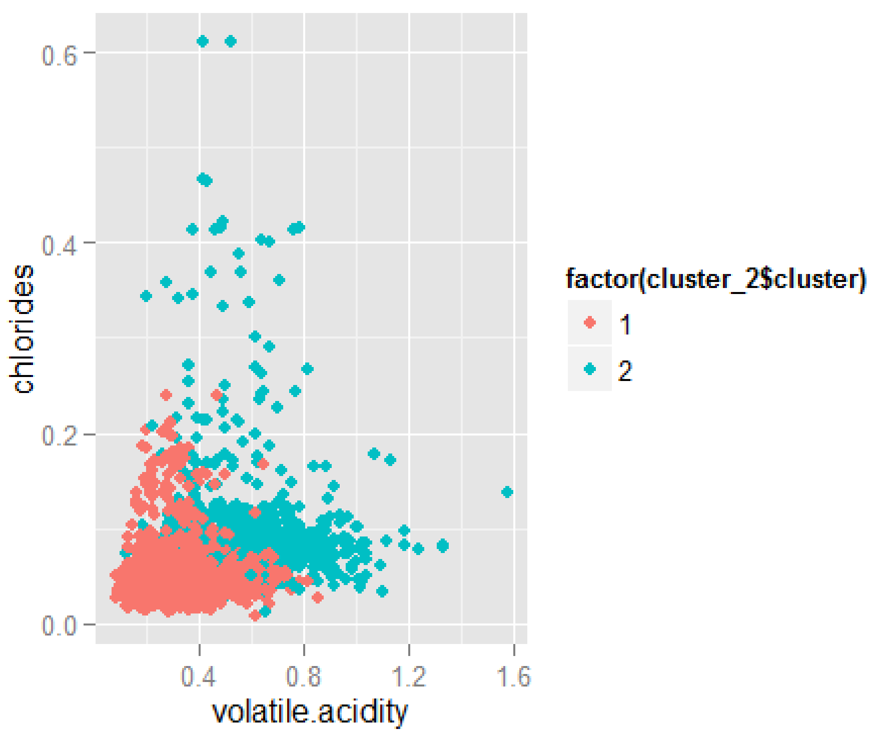
```
## [1158] 1174 1175 1176 1177 1178 1179 1180 1181 1182 1183 1184 1185 1186
## [1171] 1187 1188 1189 1190 1191 1192 1193 1194 1195 1196 1197 1198 1199
## [1184] 1200 1201 1202 1203 1204 1205 1206 1207 1208 1209 1210 1211 1212
## [1197] 1213 1214 1215 1216 1217 1218 1219 1220 1221 1222 1223 1224 1225
## [1210] 1226 1227 1228 1229 1230 1231 1232 1233 1234 1235 1237 1238 1239
## [1223] 1240 1241 1242 1243 1244 1246 1247 1248 1249 1250 1251 1252 1253
## [1236] 1254 1255 1256 1257 1258 1259 1260 1261 1262 1263 1264 1265 1266
## [1249] 1267 1268 1269 1270 1271 1272 1273 1274 1275 1276 1277 1278 1279
## [1262] 1280 1281 1282 1283 1284 1285 1286 1288 1289 1290 1291 1292 1293
## [1275] 1294 1295 1296 1297 1298 1299 1300 1301 1302 1303 1304 1305 1306
## [1288] 1307 1308 1309 1310 1311 1312 1313 1314 1315 1316 1317 1318 1319
## [1301] 1320 1321 1322 1323 1324 1325 1326 1327 1328 1329 1330 1331 1332
## [1314] 1333 1334 1335 1336 1337 1338 1339 1340 1341 1342 1343 1344 1345
## [1327] 1346 1347 1348 1349 1350 1351 1352 1353 1354 1355 1356 1357 1358
## [1340] 1359 1360 1361 1362 1363 1364 1365 1366 1367 1368 1369 1370 1371
## [1353] 1372 1373 1374 1375 1376 1377 1378 1379 1380 1381 1382 1383 1384
## [1366] 1385 1386 1387 1388 1389 1391 1392 1393 1394 1395 1396 1397 1398
## [1379] 1399 1400 1401 1402 1403 1404 1405 1406 1407 1408 1409 1410 1411
## [1392] 1412 1413 1414 1415 1416 1417 1418 1419 1420 1421 1422 1423 1424
## [1405] 1425 1426 1427 1428 1429 1430 1431 1432 1433 1434 1435 1436 1437
## [1418] 1438 1439 1440 1441 1442 1443 1444 1445 1446 1447 1448 1449 1450
## [1431] 1451 1452 1453 1454 1455 1456 1458 1459 1460 1461 1462 1463 1464
## [1444] 1465 1466 1467 1468 1469 1470 1471 1472 1473 1474 1475 1476 1477
## [1457] 1478 1479 1480 1481 1482 1483 1484 1485 1486 1487 1488 1489 1490
## [1470] 1492 1493 1494 1495 1496 1497 1498 1499 1500 1501 1502 1503 1504
## [1483] 1505 1506 1507 1508 1509 1510 1511 1512 1513 1514 1515 1516 1517
## [1496] 1518 1519 1520 1521 1522 1523 1524 1525 1526 1527 1528 1529 1530
## [1509] 1531 1532 1533 1534 1535 1536 1537 1538 1539 1540 1541 1542 1543
## [1522] 1544 1545 1546 1547 1548 1549 1550 1551 1552 1553 1554 1555 1556
## [1535] 1557 1558 1559 1560 1561 1562 1563 1564 1565 1566 1568 1569 1570
## [1548] 1571 1572 1573 1574 1576 1577 1578 1579 1580 1581 1582 1583 1584
## [1561] 1585 1586 1587 1588 1589 1590 1591 1592 1593 1594 1595 1596 1597
## [1574] 1598 1599 1715 1747 1754 1808 1830 1972 2033 2084 2106 2209 2226
## [1587] 2262 2287 2430 2434 2548 2634 2636 2637 2640 2714 2752 2817 2872
## [1600] 2986 2994 3096 3177 3308 3383 3435 3456 3465 3526 3532 3551 3624
## [1613] 3626 3692 3754 3762 3786 3949 3973 4022 4024 4075 4090 4189 4194
## [1626] 4242 4268 4381 4449 5171 5262 5448 5501 5572 5639 5813 5916 6073
## [1639] 6249 6250 6392 6415 6445
```

Plots displaying cluster association

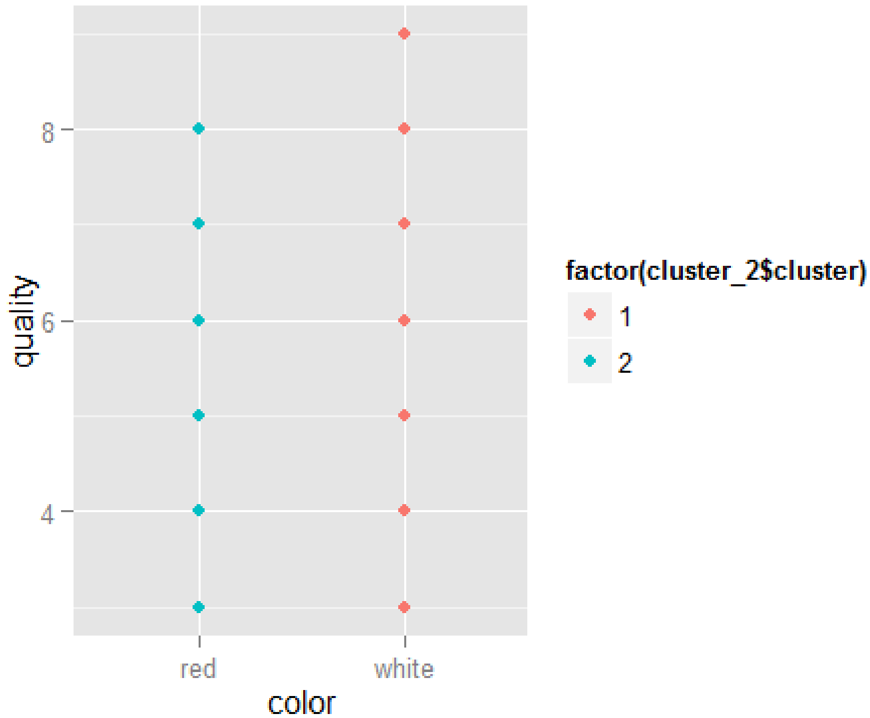
```
qplot(volatile.acidity,sulphates, data=wine, color=factor(cluster_2$cluster))
```




```
qplot(volatile.acidity, chlorides, data=wine,
color=factor(cluster_2$cluster))
```




```
qplot(color, quality, data=wine, color=factor(cluster_2$cluster))
```




```
qplot(wine$color, cluster_2$cluster, data=wine,
color=factor(cluster_2$cluster))
```

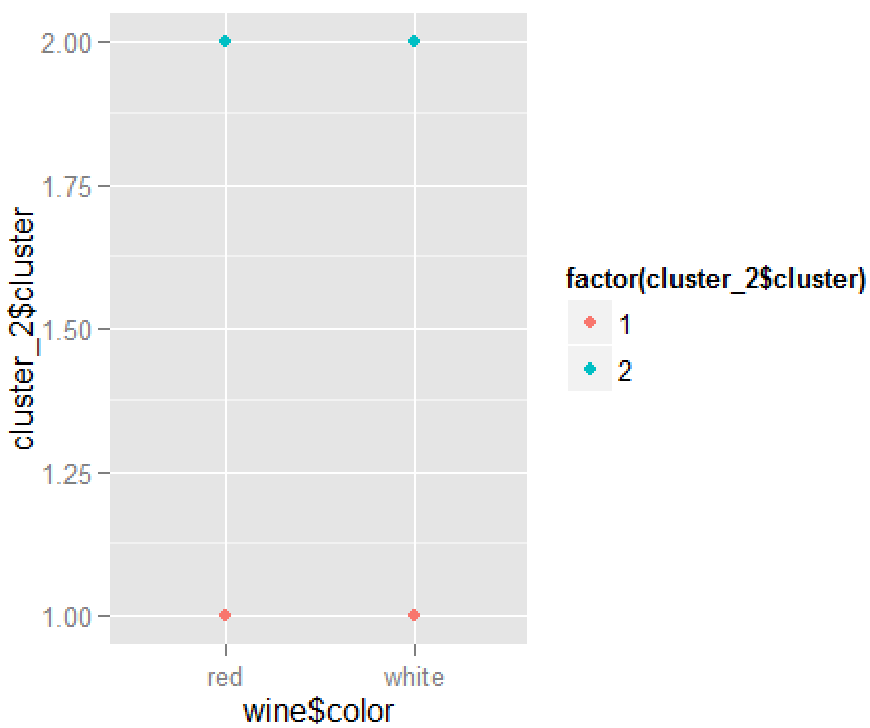


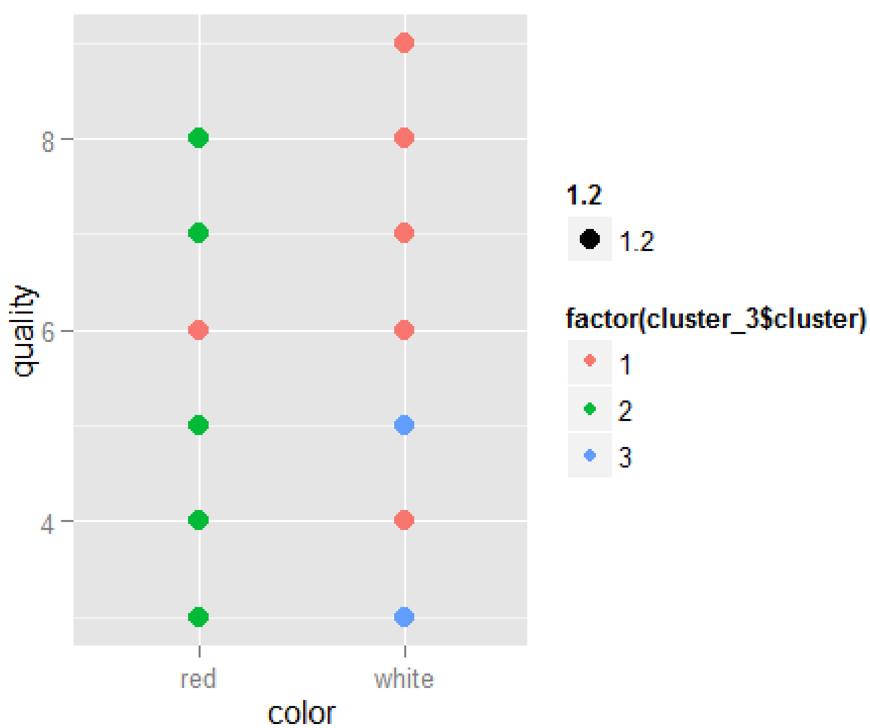
Table displaying that the clusters succesfully split red and white wine with minimal error

```
table(wine$color,cluster_2$cluster)

##
##             1    2
##   red      24 1575
##   white  4830   68
```

Quality Clustering

Cluster the data into 3 groups

```
cluster_3 = kmeans(wine_scaled, centers = 3, nstart = 50)
table(wine$quality,cluster_3$cluster)

##
##         1    2    3
##   3     8   10   12
##   4   100   68   48
##   5   638  696  804
##   6  1371  622  843
##   7   740  182  157
##   8   148   15   30
##   9     4    0    1

qplot(color, quality, data=wine, color=factor(cluster_3$cluster),cex= 1.2)
```



It is dificult to distinguish the wines by quality.

PCA

Run PCA on the data and look at the result

```
pca_wine = prcomp(wine_num, scale.=TRUE)
pca_wine
```

```
## Standard deviations:
##  [1] 1.7406518 1.5791852 1.2475364 0.9851660 0.8484544 0.7793021 0.7232971
##  [8] 0.7081739 0.5805377 0.4771748 0.1811927
## 
## Rotation:
##                              PC1         PC2         PC3         PC4
## fixed.acidity        -0.23879890  0.33635454 -0.43430130  0.16434621
## volatile.acidity     -0.38075750  0.11754972  0.30725942  0.21278489
## citric.acid           0.15238844  0.18329940 -0.59056967 -0.26430031
## residual.sugar        0.34591993  0.32991418  0.16468843  0.16744301
## chlorides            -0.29011259  0.31525799  0.01667910 -0.24474386
## free.sulfur.dioxide   0.43091401  0.07193260  0.13422395 -0.35727894
## total.sulfur.dioxide  0.48741806  0.08726628  0.10746230 -0.20842014
## density              -0.04493664  0.58403734  0.17560555  0.07272496
## pH                   -0.21868644 -0.15586900  0.45532412 -0.41455110
## sulphates            -0.29413517  0.19171577 -0.07004248 -0.64053571
## alcohol              -0.10643712 -0.46505769 -0.26110053 -0.10680270
##                             PC5         PC6         PC7          PC8
## fixed.acidity        -0.1474804 -0.20455371 -0.28307944  0.401235645
## volatile.acidity      0.1514560 -0.49214307 -0.38915976 -0.087435088
## citric.acid          -0.1553487  0.22763380 -0.38128504 -0.293412336
## residual.sugar       -0.3533619 -0.23347775  0.21797554 -0.524872935
## chlorides             0.6143911  0.16097639 -0.04606816 -0.471516850
## free.sulfur.dioxide   0.2235323 -0.34005140 -0.29936325  0.207807585
## total.sulfur.dioxide  0.1581336 -0.15127722 -0.13891032  0.128621319
## density              -0.3065613  0.01874307 -0.04675897  0.004831136
## pH                   -0.4533764  0.29657890 -0.41890702 -0.028643277
## sulphates            -0.1365769 -0.29692579  0.52534311  0.165818022
## alcohol              -0.1888920 -0.51837780 -0.10410343 -0.399233887
##                             PC9         PC10          PC11
## fixed.acidity         0.3440567 -0.281267685 -0.3346792663
## volatile.acidity     -0.4969327  0.152176731 -0.0847718098
## citric.acid          -0.4026887  0.234463340  0.0011089514
## residual.sugar        0.1080032 -0.001372773 -0.4497650778
## chlorides             0.2964437 -0.196630217 -0.0434375867
## free.sulfur.dioxide   0.3666563  0.480243340  0.0002125351
## total.sulfur.dioxide -0.3206955 -0.713663486  0.0626848131
## density               0.1128800 -0.003908289  0.7151620723
## pH                    0.1278367 -0.141310977 -0.2063605036
## sulphates            -0.2077642  0.045959499 -0.0772024671
## alcohol               0.2518903 -0.205053085  0.3357018784
```

See some statistics and plots related to the PCA

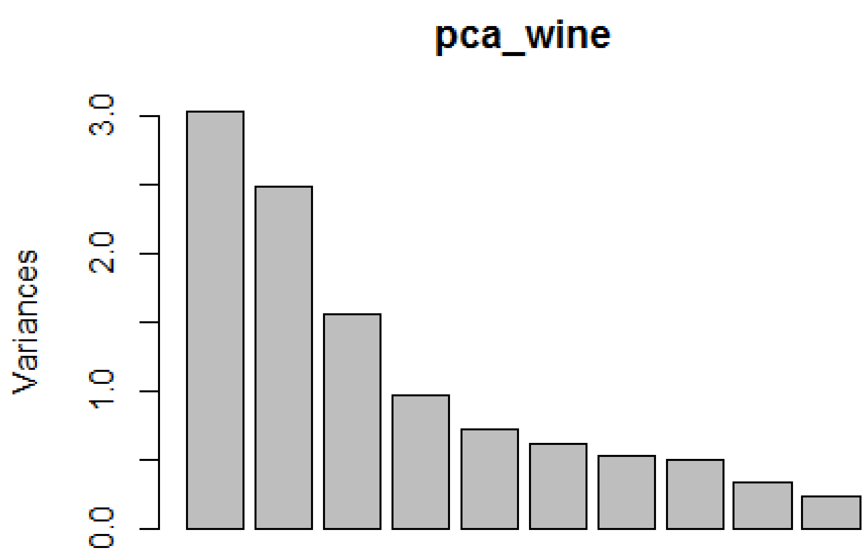
```r
summary(pca_wine)
```

```
## Importance of components:
##                           PC1    PC2    PC3     PC4     PC5     PC6
## Standard deviation     1.7407 1.5792 1.2475 0.98517 0.84845 0.77930
## Proportion of Variance 0.2754 0.2267 0.1415 0.08823 0.06544 0.05521
## Cumulative Proportion  0.2754 0.5021 0.6436 0.73187 0.79732 0.85253
##                            PC7     PC8     PC9   PC10    PC11
## Standard deviation     0.72330 0.70817 0.58054 0.4772 0.18119
## Proportion of Variance 0.04756 0.04559 0.03064 0.0207 0.00298
## Cumulative Proportion  0.90009 0.94568 0.97632 0.9970 1.00000
```

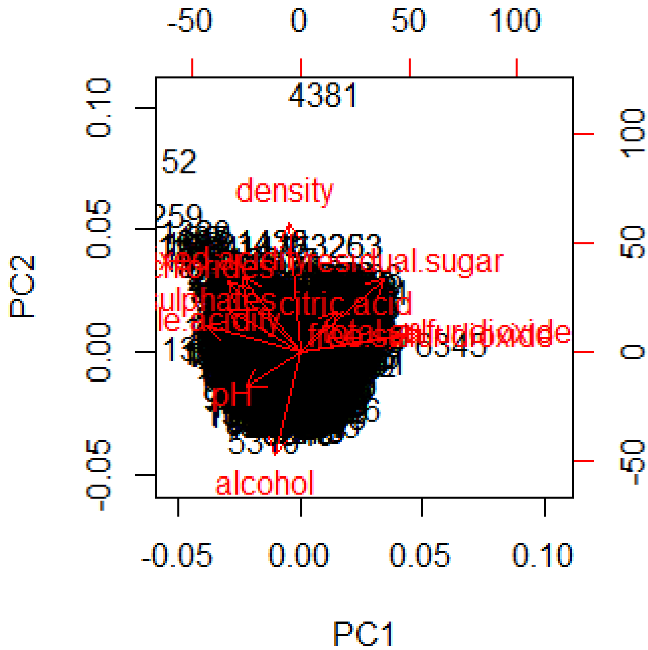
```r
sum((pca_wine$sdev)^2)
```

```
## [1] 11
```

```r
plot(pca_wine)
```

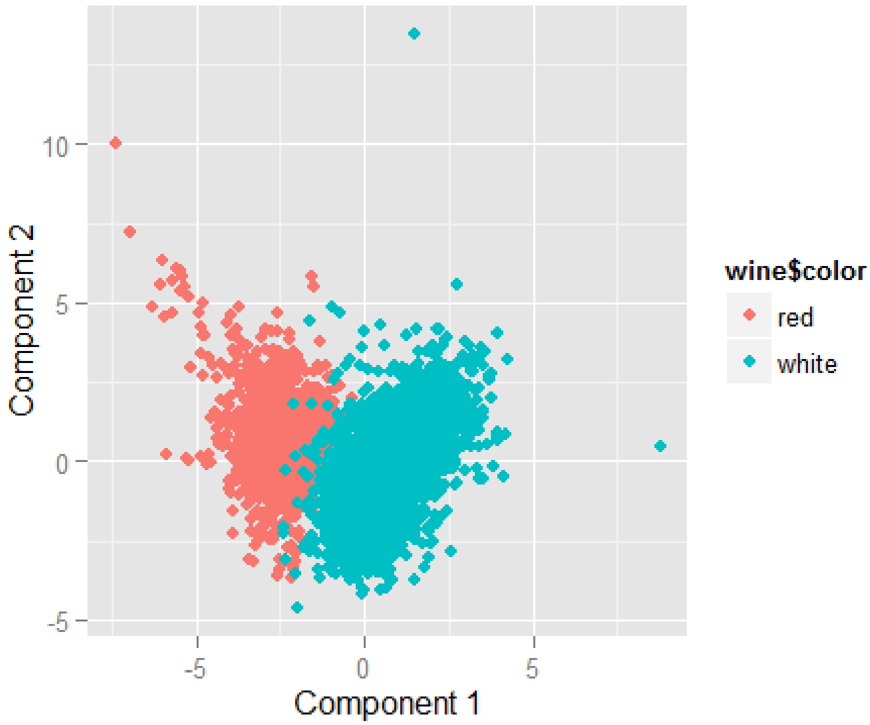



```r
biplot(pca_wine)
```



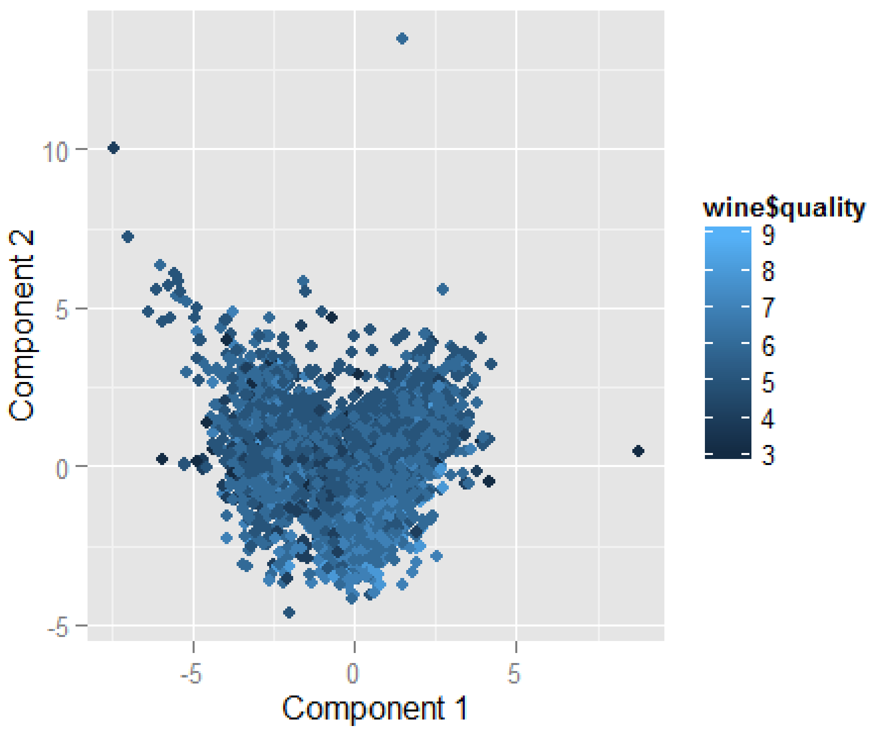
By looking at the score and plotting them, we can again see the distinction from red and white wines

```
scores = pca_wine$x
head(scores)

##             PC1       PC2       PC3       PC4        PC5        PC6
## [1,] -3.205749 0.4164913  2.722027 0.7967162 -0.2028619  0.2273453
## [2,] -3.038817 1.1073769  2.046795 0.7701656  1.3225536 -1.6549941
## [3,] -3.071657 0.8788968  1.742445 0.8021955  0.7620531 -0.8483083
## [4,] -1.571141 2.1123820 -2.592717 0.2927620 -0.6046542  0.7132533
## [5,] -3.205749 0.4164913  2.722027 0.7967162 -0.2028619  0.2273453
## [6,] -3.011934 0.3893675  2.669970 0.6861020 -0.2077957  0.2928529
##              PC7       PC8         PC9        PC10        PC11
## [1,] -0.32552850 0.5672348  0.07122341  0.10803795  0.02745798
## [2,]  0.05955408 0.5145630 -0.42909559  0.26812827 -0.01547017
## [3,]  0.16765673 0.4209200 -0.27101087  0.08682522  0.05414179
## [4,] -0.85115161 0.9295970  0.54936730 -0.11665069 -0.10373671
## [5,] -0.32552850 0.5672348  0.07122341  0.10803795  0.02745798
## [6,] -0.28272294 0.6500382  0.18849800  0.05506242  0.06542536

nrow(scores)

## [1] 6497

qplot(scores[,1], scores[,2], color=wine$color, xlab='Component 1',
ylab='Component 2')
```



Again when plotting to see quality, it is dificult to see any distinction.

```
qplot(scores[,1], scores[,2], color=wine$quality, xlab='Component 1',
ylab='Component 2')
```



In conclusion I beleive clustering is more useful in evaluating this data. The plots formed from clustering claerly seperated red and white wines. Additionally by using the table function we were able to see that clustering distinguished between the wines with a high level of precision.

(4) Market Segmentation

K-Means clustering

Read in the data

```
twitter = read.csv('social_marketing.csv')

head(twitter)

##           X chatter current_events travel photo_sharing uncategorized
## 1 hmjoe4g3k       2              0      2             2             2
## 2 clk1m5w8s       3              3      2             1             1
## 3 jcsovtak3       6              3      4             3             1
## 4 3oeb4hiln       1              5      2             2             0
## 5 fd75x1vgk       5              2      0             6             1
## 6 h6nvj91yp       6              4      2             7             0
##   tv_film sports_fandom politics food family home_and_garden music news
## 1       1             1        0    4      1               2     0    0
## 2       1             4        1    2      2               1     0    0
```

```
## 3       5             0        2    1      1               1     1    1
## 4       1             0        1    0      1               0     0    0
## 5       0             0        2    0      1               0     0    0
## 6       1             1        0    2      1               1     1    0
##   online_gaming shopping health_nutrition college_uni sports_playing
## 1             0        1               17           0              2
## 2             0        0                0           0              1
## 3             0        2                0           0              0
## 4             0        0                0           1              0
## 5             3        2                0           4              0
## 6             0        5                0           0              0
##   cooking eco computers business outdoors crafts automotive art religion
## 1       5   1         1        0        2      1          0   0        1
## 2       0   0         0        1        0      2          0   0        0
## 3       2   1         0        0        0      2          0   8        0
## 4       0   0         0        1        0      3          0   2        0
## 5       1   0         1        0        1      0          0   0        0
## 6       0   0         1        1        0      0          1   0        0
##   beauty parenting dating school personal_fitness fashion small_business
## 1      0         1      1      0               11       0              0
## 2      0         0      1      4                0       0              0
## 3      1         0      1      0                0       1              0
## 4      1         0      0      0                0       0              0
## 5      0         0      0      0                0       0              1
## 6      0         0      0      0                0       0              0
##   spam adult
## 1    0     0
## 2    0     0
## 3    0     0
## 4    0     0
## 5    0     0
## 6    0     0
```

```r
names(twitter)
```

```
##  [1] "X"                  "chatter"          "current_events"
##  [4] "travel"             "photo_sharing"    "uncategorized"
##  [7] "tv_film"            "sports_fandom"    "politics"
## [10] "food"               "family"           "home_and_garden"
## [13] "music"              "news"             "online_gaming"
## [16] "shopping"           "health_nutrition" "college_uni"
## [19] "sports_playing"     "cooking"          "eco"
## [22] "computers"          "business"         "outdoors"
## [25] "crafts"             "automotive"       "art"
## [28] "religion"           "beauty"           "parenting"
## [31] "dating"             "school"           "personal_fitness"
## [34] "fashion"            "small_business"   "spam"
## [37] "adult"
```

Remove the 1st and last 2 columns of the dataset and scale the data.

```
twitter_num = twitter [,(2:35)]
twitter_scaled = scale(twitter_num, center = TRUE, scale = TRUE)
```

cluster the data using 5 centers, in hopes of distinguishing market segments.

```
cluster_twitter = kmeans(twitter_scaled, centers = 5, nstart = 200)
```

Capture the mean and SD of the scaled data.

```
sigma_twitter = attr(twitter_scaled,"scaled:scale")
mu_twitter = attr(twitter_scaled,"scaled:center")
```

Unscale the data.

```
cluster_twitter$center

##        chatter current_events      travel photo_sharing uncategorized
## 1 -0.086222413     0.11809608 -0.09771495   -0.06537001   -0.07560096
## 2  0.722175675     0.27442218 -0.03596486    1.03832015    0.45534783
## 3 -0.212834402    -0.12948720 -0.23381547   -0.31620751   -0.16643598
## 4 -0.006995531     0.10556173  1.83977588   -0.10723104   -0.04382044
## 5 -0.084492666    -0.01124003 -0.15545173   -0.04798195    0.14853649
##        tv_film sports_fandom   politics        food      family
## 1  0.000746473     2.0470620 -0.1982928  1.81765091  1.49765506
## 2  0.485228283    -0.1645516 -0.1310832 -0.15553966  0.03722871
## 3 -0.149523564    -0.2977550 -0.2727615 -0.36584951 -0.27118944
## 4  0.033096281     0.1920158  2.4282822  0.03297433  0.05045762
## 5 -0.104380041    -0.1939706 -0.1810003  0.43202406 -0.07556437
##   home_and_garden       music        news online_gaming     shopping
## 1       0.1706871  0.04803399 -0.06700095    0.02473461 -0.001135387
## 2       0.2660681  0.57282236 -0.13054926    0.43242891  0.742711633
## 3      -0.1701953 -0.20187397 -0.24809584   -0.12679472 -0.243105271
## 4       0.1185947 -0.05033662  1.93533117   -0.07604167 -0.057068483
## 5       0.1418000  0.02622923 -0.03255397   -0.06324663 -0.007390447
##   health_nutrition college_uni sports_playing     cooking         eco
## 1       -0.1528754 -0.03268345     0.14438408 -0.08800954  0.17248722
## 2       -0.1815311  0.58926171     0.50358625  0.86228797  0.23181896
## 3       -0.3295290 -0.15720684    -0.20697001 -0.33998540 -0.23646305
## 4       -0.2023987 -0.03276814     0.02766946 -0.19240063  0.09727734
## 5        2.1505827 -0.15849832     0.02193048  0.43667699  0.52817655
##     computers   business    outdoors      crafts  automotive         art
## 1  0.07670276  0.1215802 -0.06801627  0.70338638  0.17590291  0.11089822
## 2 -0.02412705  0.3721702 -0.11253202  0.29050312  0.08501058  0.43825776
## 3 -0.25278692 -0.2097674 -0.31512163 -0.25859111 -0.20677952 -0.15790482
## 4  1.64069987  0.3293340  0.10575747  0.10738581  1.07469608 -0.04970671
## 5 -0.07939718  0.0374073  1.66131375  0.08062137 -0.12643014 -0.01768315
##      religion     beauty   parenting      dating      school
## 1  2.25268080  0.3124905  2.12069484 -0.01192335  1.65716669
## 2 -0.16518697  0.8599830 -0.13690144  0.30780026  0.15654677
## 3 -0.30436878 -0.2904203 -0.31199940 -0.17031941 -0.30572877
## 4 -0.03036794 -0.1505644  0.02142103  0.20654026 -0.04530884
## 5 -0.16501662 -0.1669719 -0.10269878  0.16158299 -0.16709797
```

```
##   personal_fitness     fashion small_business
## 1      -0.09784654  0.02696846     0.09556896
## 2      -0.14604173  0.96454926     0.44854802
## 3      -0.34409012 -0.29434889    -0.18012218
## 4      -0.19706439 -0.15869840     0.22739613
## 5       2.11143052 -0.07063281    -0.12811374
```

```
cluster_twitter$center[1,]*sigma_twitter + mu_twitter
```

```
##          chatter   current_events           travel    photo_sharing 
##        4.0944669        1.6761134        1.3616734        2.5182186 
##    uncategorized          tv_film    sports_fandom         politics 
##        0.7422402        1.0715250        6.0175439        1.1875843 
##             food           family  home_and_garden            music 
##        4.6248313        2.5600540        0.6464238        0.7287449 
##             news    online_gaming         shopping health_nutrition 
##        1.0647773        1.2753036        1.3873144        1.8798920 
##      college_uni   sports_playing          cooking              eco 
##        1.4547908        0.7800270        1.6963563        0.6450742 
##        computers         business         outdoors           crafts 
##        0.7395412        0.5074224        0.7004049        1.0904184 
##       automotive              art         religion           beauty 
##        1.0701754        0.9055331        5.4089069        1.1201080 
##        parenting           dating           school personal_fitness 
##        4.1349528        0.6896086        2.7368421        1.2267206 
##          fashion   small_business 
##        1.0458839        0.3954116
```

```
cluster_twitter$center[2,]*sigma_twitter + mu_twitter
```

```
##          chatter   current_events           travel    photo_sharing 
##        6.9474053        1.8744741        1.5028050        5.5329593 
##    uncategorized          tv_film    sports_fandom         politics 
##        1.2391304        1.8751753        1.2384292        1.3913043 
##             food           family  home_and_garden            music 
##        1.1213184        0.9060309        0.7166900        1.2692847 
##             news    online_gaming         shopping health_nutrition 
##        0.9312763        2.3709677        2.7328191        1.7510519 
##      college_uni   sports_playing          cooking              eco 
##        3.2566620        1.1304348        4.9558205        0.6907433 
##        computers         business         outdoors           crafts 
##        0.6206171        0.6809257        0.6465638        0.7531557 
##       automotive              art         religion           beauty 
##        0.9460028        1.4389902        0.7791024        1.8471248 
##        parenting           dating           school personal_fitness 
##        0.7138850        1.2594670        0.9537167        1.1107994 
##          fashion   small_business 
##        2.7601683        0.6136045
```

See attributes are emphasized in each cluster to facilitate targeting

```r
#Young women. Care about fashion, beauty, cooking, shopping, and photo
sharing
rbind(cluster_twitter$center[1,],cluster_twitter$center[1,]*sigma_twitter +
mu_twitter)
```

```
##          chatter current_events      travel photo_sharing uncategorized
## [1,] -0.08622241      0.1180961 -0.09771495   -0.06537001   -0.07560096
## [2,]  4.09446694      1.6761134  1.36167341    2.51821862    0.74224022
##          tv_film sports_fandom   politics     food   family
## [1,] 0.000746473      2.047062 -0.1982928 1.817651 1.497655
## [2,] 1.071524966      6.017544  1.1875843 4.624831 2.560054
##      home_and_garden      music        news online_gaming     shopping
## [1,]       0.1706871 0.04803399 -0.06700095    0.02473461 -0.001135387
## [2,]       0.6464238 0.72874494  1.06477733    1.27530364  1.387314440
##      health_nutrition college_uni sports_playing     cooking       eco
## [1,]       -0.1528754 -0.03268345      0.1443841 -0.08800954 0.1724872
## [2,]        1.8798920  1.45479082      0.7800270  1.69635628 0.6450742
##       computers  business    outdoors    crafts automotive       art
## [1,] 0.07670276 0.1215802 -0.06801627 0.7033864  0.1759029 0.1108982
## [2,] 0.73954116 0.5074224  0.70040486 1.0904184  1.0701754 0.9055331
##      religion    beauty parenting      dating   school personal_fitness
## [1,] 2.252681 0.3124905  2.120695 -0.01192335 1.657167      -0.09784654
## [2,] 5.408907 1.1201080  4.134953  0.68960864 2.736842       1.22672065
##         fashion small_business
## [1,] 0.02696846     0.09556896
## [2,] 1.04588394     0.39541161
```

```r
#Your classic young parent (sports, food, family, religion, and parenting)
rbind(cluster_twitter$center[2,],cluster_twitter$center[2,]*sigma_twitter +
mu_twitter)
```

```
##        chatter current_events      travel photo_sharing uncategorized
## [1,] 0.7221757      0.2744222 -0.03596486      1.038320     0.4553478
## [2,] 6.9474053      1.8744741  1.50280505      5.532959     1.2391304
##        tv_film sports_fandom   politics       food     family
## [1,] 0.4852283    -0.1645516 -0.1310832 -0.1555397 0.03722871
## [2,] 1.8751753     1.2384292  1.3913043  1.1213184 0.90603086
##      home_and_garden     music       news online_gaming  shopping
## [1,]       0.2660681 0.5728224 -0.1305493     0.4324289 0.7427116
## [2,]       0.7166900 1.2692847  0.9312763     2.3709677 2.7328191
##      health_nutrition college_uni sports_playing  cooking       eco
## [1,]       -0.1815311   0.5892617      0.5035862 0.862288 0.2318190
## [2,]        1.7510519   3.2566620      1.1304348 4.955820 0.6907433
##        computers  business   outdoors    crafts automotive       art
## [1,] -0.02412705 0.3721702 -0.1125320 0.2905031 0.08501058 0.4382578
## [2,]  0.62061711 0.6809257  0.6465638 0.7531557 0.94600281 1.4389902
##        religion   beauty  parenting    dating    school personal_fitness
## [1,] -0.1651870 0.859983 -0.1369014 0.3078003 0.1565468       -0.1460417
## [2,]  0.7791024 1.847125  0.7138850 1.2594670 0.9537167        1.1107994
##        fashion small_business
```

```
## [1,] 0.9645493      0.4485480
## [2,] 2.7601683      0.6136045
```

```
#Average No-desciptive cluster
rbind(cluster_twitter$center[3,],cluster_twitter$center[3,]*sigma_twitter +
mu_twitter)
```

```
##         chatter current_events     travel photo_sharing uncategorized
## [1,] -0.2128344     -0.1294872 -0.2338155    -0.3162075     -0.166436
## [2,]  3.6476373      1.3619573  1.0506117     1.8330535      0.657232
##         tv_film sports_fandom   politics       food     family
## [1,] -0.1495236    -0.2977550 -0.2727615 -0.3658495 -0.2711894
## [2,]  0.8222595     0.9505877  0.9618614  0.7479012  0.5567282
##      home_and_garden      music       news online_gaming   shopping
## [1,]      -0.1701953 -0.2018740 -0.2480958    -0.1267947 -0.2431053
## [2,]       0.3952986  0.4713361  0.6843368     0.8680739  0.9496282
##      health_nutrition college_uni sports_playing    cooking       eco
## [1,]        -0.329529  -0.1572068     -0.2069700 -0.3399854 -0.236463
## [2,]         1.085632   1.0940273      0.4372751  0.8320940  0.330295
##       computers   business   outdoors     crafts automotive        art
## [1,] -0.2527869 -0.2097674 -0.3151216 -0.2585911 -0.2067795 -0.1579048
## [2,]  0.3509235  0.2780043  0.4015351  0.3046294  0.5473735  0.4674982
##        religion     beauty  parenting     dating     school
## [1,] -0.3043688 -0.2904203 -0.3119994 -0.1703194 -0.3057288
## [2,]  0.5125929  0.3195011  0.4485488  0.4072919  0.4044135
##      personal_fitness    fashion small_business
## [1,]       -0.3440901 -0.2943489     -0.1801222
## [2,]        0.6344447  0.4583833      0.2249940
```

```
#Athletiic/Healthy Cluster (Nutrition, outdoors, and personal fitness)
rbind(cluster_twitter$center[4,],cluster_twitter$center[4,]*sigma_twitter +
mu_twitter)
```

```
##           chatter current_events   travel photo_sharing uncategorized
## [1,] -0.006995531      0.1055617 1.839776     -0.107231   -0.04382044
## [2,]  4.374068554      1.6602086 5.789866      2.403875    0.77198212
##         tv_film sports_fandom politics       food     family
## [1,] 0.03309628     0.1920158 2.428282 0.03297433 0.05045762
## [2,] 1.12518629     2.0089419 9.149031 1.45603577 0.92101341
##      home_and_garden       music     news online_gaming    shopping
## [1,]       0.1185947 -0.05033662 1.935331   -0.07604167 -0.05706848
## [2,]       0.6080477  0.62742176 5.271237    1.00447094  1.28614009
##      health_nutrition college_uni sports_playing    cooking        eco
## [1,]       -0.2023987 -0.03276814     0.02766946 -0.1924006 0.09727734
## [2,]        1.6572280  1.45454545     0.66616990  1.3383010 0.58718331
##      computers  business  outdoors    crafts automotive         art
## [1,]  1.640700 0.3293340 0.1057575 0.1073858   1.074696 -0.04970671
## [2,]  2.584203 0.6512668 0.9105812 0.6035768   2.298063  0.64381520
##         religion     beauty  parenting    dating      school
## [1,] -0.03036794 -0.1505644 0.02142103 0.2065403 -0.04530884
## [2,]  1.03725782  0.5052161 0.95380030 1.0789866  0.71385991
```

```
##      personal_fitness    fashion small_business
## [1,]       -0.1970644 -0.1586984      0.2273961
## [2,]        0.9880775  0.7064083      0.4769001
```

```r
#worldly and current cluster (travel, politics, news, automotive, computers)
rbind(cluster_twitter$center[5,],cluster_twitter$center[5,]*sigma_twitter +
mu_twitter)
```

```
##          chatter current_events     travel photo_sharing uncategorized
## [1,] -0.08449267    -0.01124003 -0.1554517   -0.04798195     0.1485365
## [2,]  4.10057143     1.51200000  1.2297143    2.56571429     0.9520000
##         tv_film sports_fandom   politics      food      family
## [1,] -0.1043800    -0.1939706 -0.1810003 0.4320241 -0.07556437
## [2,]  0.8971429     1.1748571  1.2400000 2.1645714  0.77828571
##      home_and_garden      music        news online_gaming     shopping
## [1,]       0.1418000 0.02622923 -0.03255397   -0.06324663 -0.007390447
## [2,]       0.6251429 0.70628571  1.13714286    1.03885714  1.376000000
##      health_nutrition college_uni sports_playing  cooking       eco
## [1,]         2.150583  -0.1584983     0.02193048 0.436677 0.5281765
## [2,]        12.236571   1.0902857     0.66057143 3.496000 0.9188571
##        computers  business outdoors     crafts automotive         art
## [1,] -0.07939718 0.0374073 1.661314 0.08062137 -0.1264301 -0.01768315
## [2,]  0.55542857 0.4491429 2.792000 0.58171429  0.6571429  0.69600000
##        religion     beauty  parenting    dating     school
## [1,] -0.1650166 -0.1669719 -0.1026988 0.1615830 -0.1670980
## [2,]  0.7794286  0.4834286  0.7657143 0.9988571  0.5691429
##      personal_fitness     fashion small_business
## [1,]         2.111431 -0.07063281     -0.1281137
## [2,]         6.540571  0.86742857      0.2571429
```

Conclusion

By using K-Menas clustering with 5 centers I was able to successfully group the twitter users into distinct groups. The clusters found were; Young women, Parents, Athletic people, contemporaries, and then a group that was relatively average accross all categories. I think these clusters could provide useful marketing insights to NutrientH20.