Assignment_PM

Sanchit Shaleen

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Q1 Exploratory analysis

```
library(ggplot2)
dataGeorgia<-read.csv("F:/Predictive Modelling(JScott)/PredictiveModelling/STA380/dat
a/georgia2000.csv")
dataGeorgia[,"VoteUnderCount"]<-(dataGeorgia$ballots - dataGeorgia$votes)
dataGeorgia$poor<-as.factor(dataGeorgia$poor)
```

Part (a)

Whether voting certain kinds of voting equipment lead to higher rates of undercount?

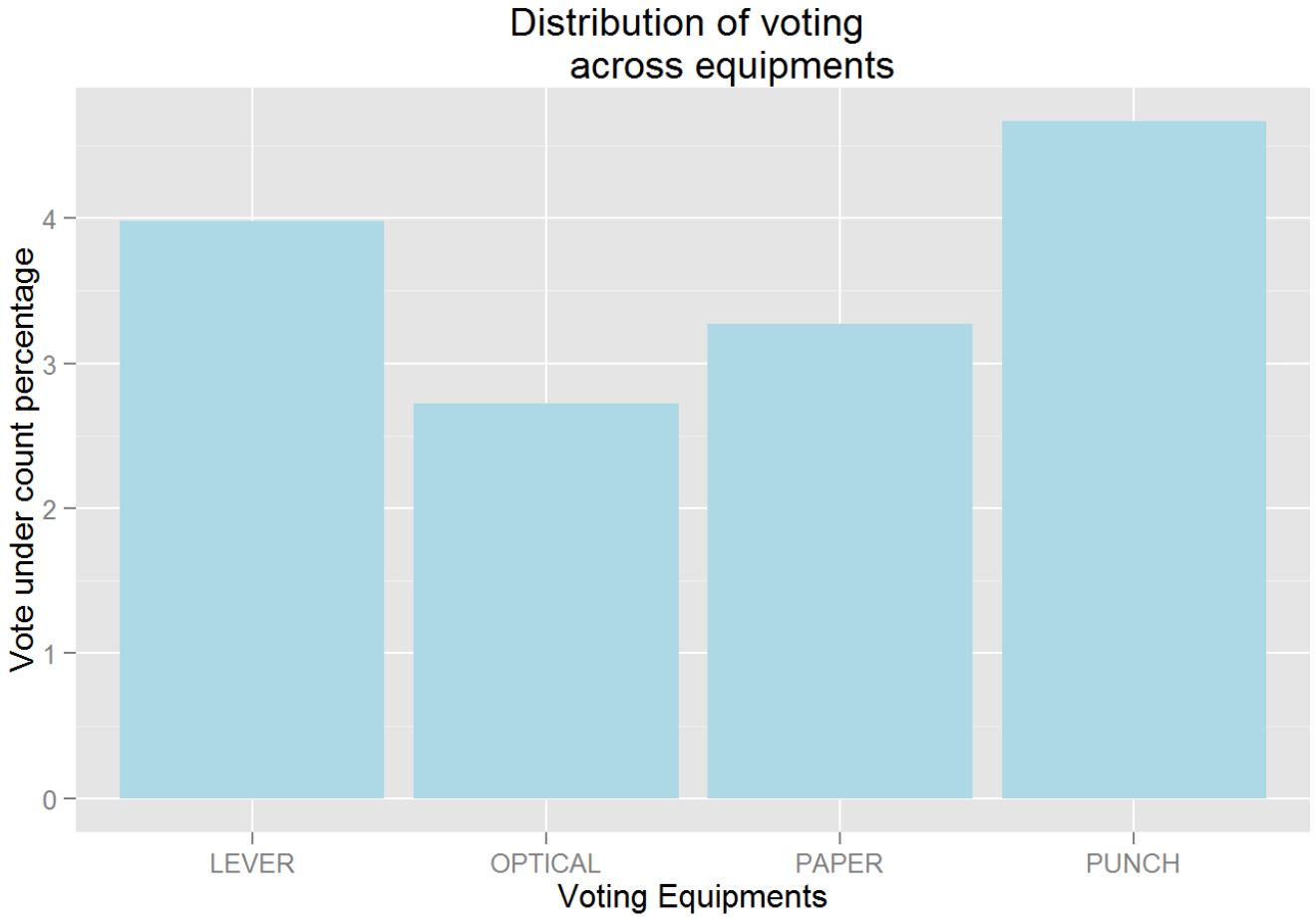
Applying aggregate function to calculate the total ballot count and vote under-count over different equipments

```
nuc<-aggregate(dataGeorgia$VoteUnderCount ~ dataGeorgia$equip, data = dataGeorgia, sum)
nbc<-aggregate(dataGeorgia$ballots ~ dataGeorgia$equip, data = dataGeorgia, sum)
```

Merging the aggregated data

```
ndf<-merge(nbc,nuc,by=intersect(names(nbc), names(nuc)))
ndf$VoteUnderCountPercent<-ndf[,3]/ndf[,2] *100
```

Distribution of voting across equipments



As per the analysis, there seems to be a higher under-count percentage when the voting is is done using Punch Device.

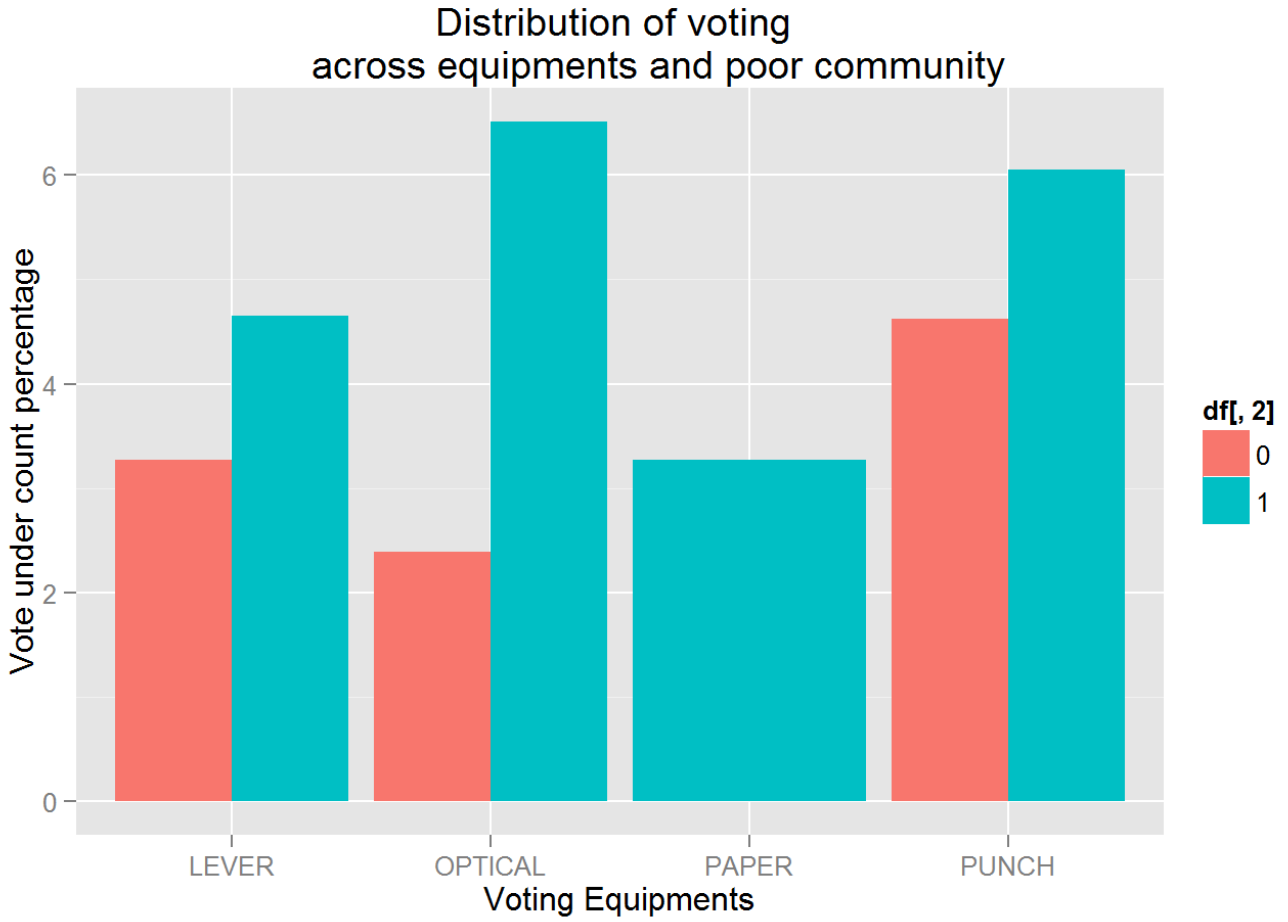
Part(b) Whether we should worry that this effect has a disparate impact on poor and minority communities?

** Impact on Poor **

```
uc<-aggregate(dataGeorgia$VoteUnderCount ~ dataGeorgia$equip+dataGeorgia$poor, data = d
ataGeorgia, sum)
bc<-aggregate(dataGeorgia$ballots ~ dataGeorgia$equip+dataGeorgia$poor, data = dataGeor
gia, sum)
```

Merging the aggregated data into a new data frame and adding a new column named UnderCountPercent to it.

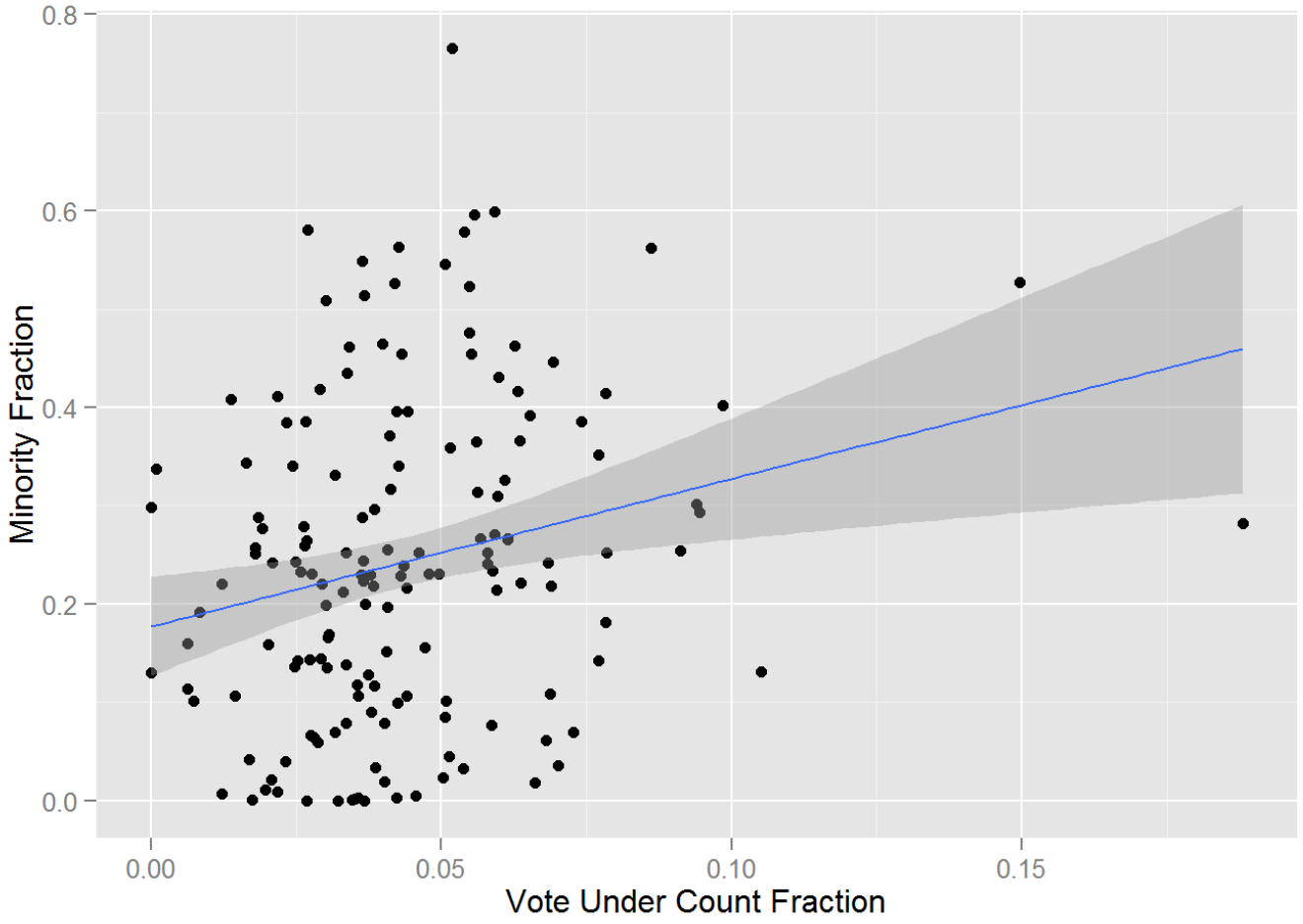
```
df = data.frame()
df<-merge(bc,uc,by=intersect(names(bc), names(uc)))
df$VoteUnderCountPercent<-df[,4]/df[,3] *100
```



Analysis: There seems to be a higher under-count percentage amongst poor people using Optical device for casting their vote

** Impact on Minority ** There's a weak co-relation between Minority community and Vote undercount

```
qplot(dataGeorgia$VoteUnderCount/dataGeorgia$ballots,dataGeorgia$perAA,geom=c("poin
t","smooth"),method="lm",
xlab="Vote Under Count Fraction",ylab="Minority Fraction")
```



Ques 2 Bootstrapping

Part(a)

```
library(mosaic)
library(fImport)
library(foreach)
set.seed(10)
```

Import a few stocks

```
mystocks = c("SPY", "TLT", "LQD","EEM","VNQ")
myprices = yahooSeries(mystocks, from='2011-01-01', to='2015-08-05')
```

A helper function for calculating percent returns from a Yahoo Series

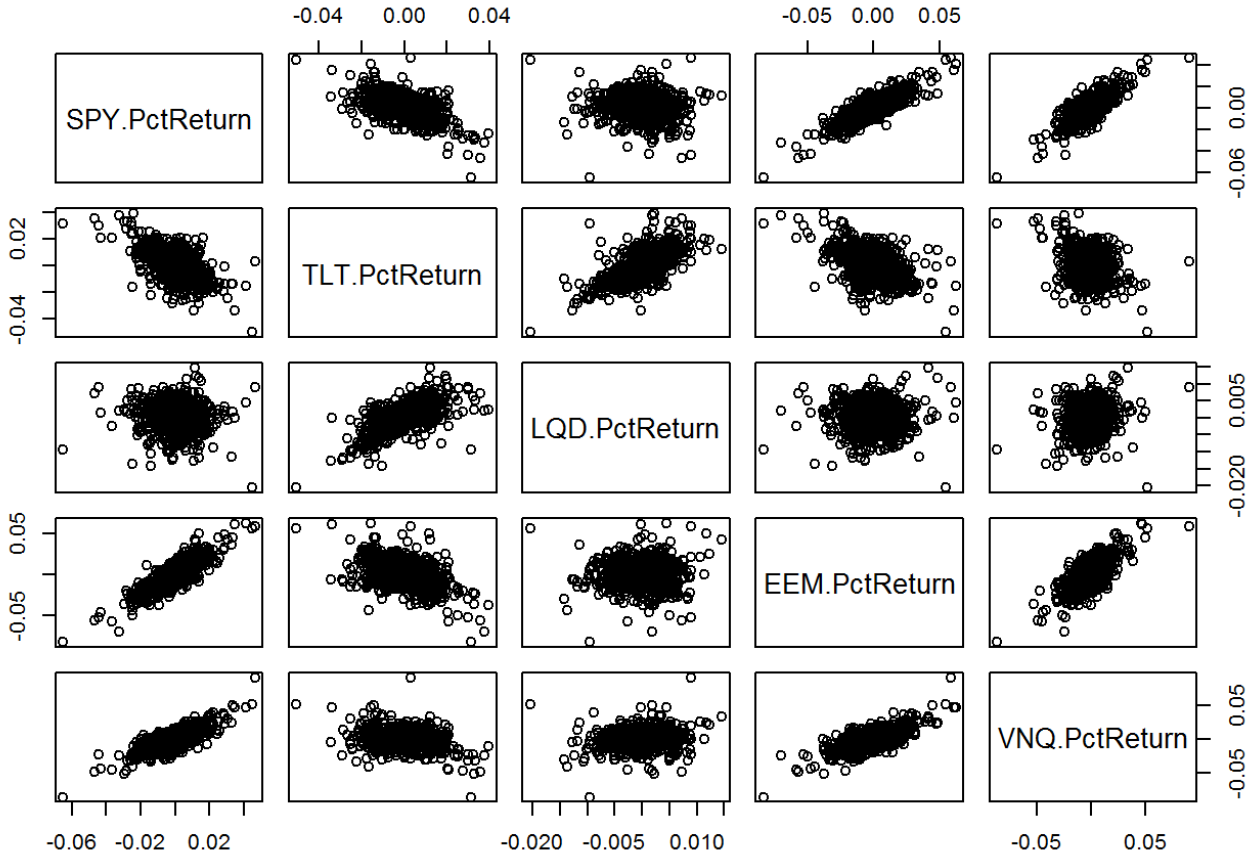
```
YahooPricesToReturns = function(series) {
  mycols = grep('Adj.Close', colnames(series))
  closingprice = series[,mycols]
  N = nrow(closingprice)
  percentreturn = as.data.frame(closingprice[2:N,]) / as.data.frame(closingprice[1:(N-
1),]) - 1
  mynames = strsplit(colnames(percentreturn), '.', fixed=TRUE)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

Compute the returns from the closing prices

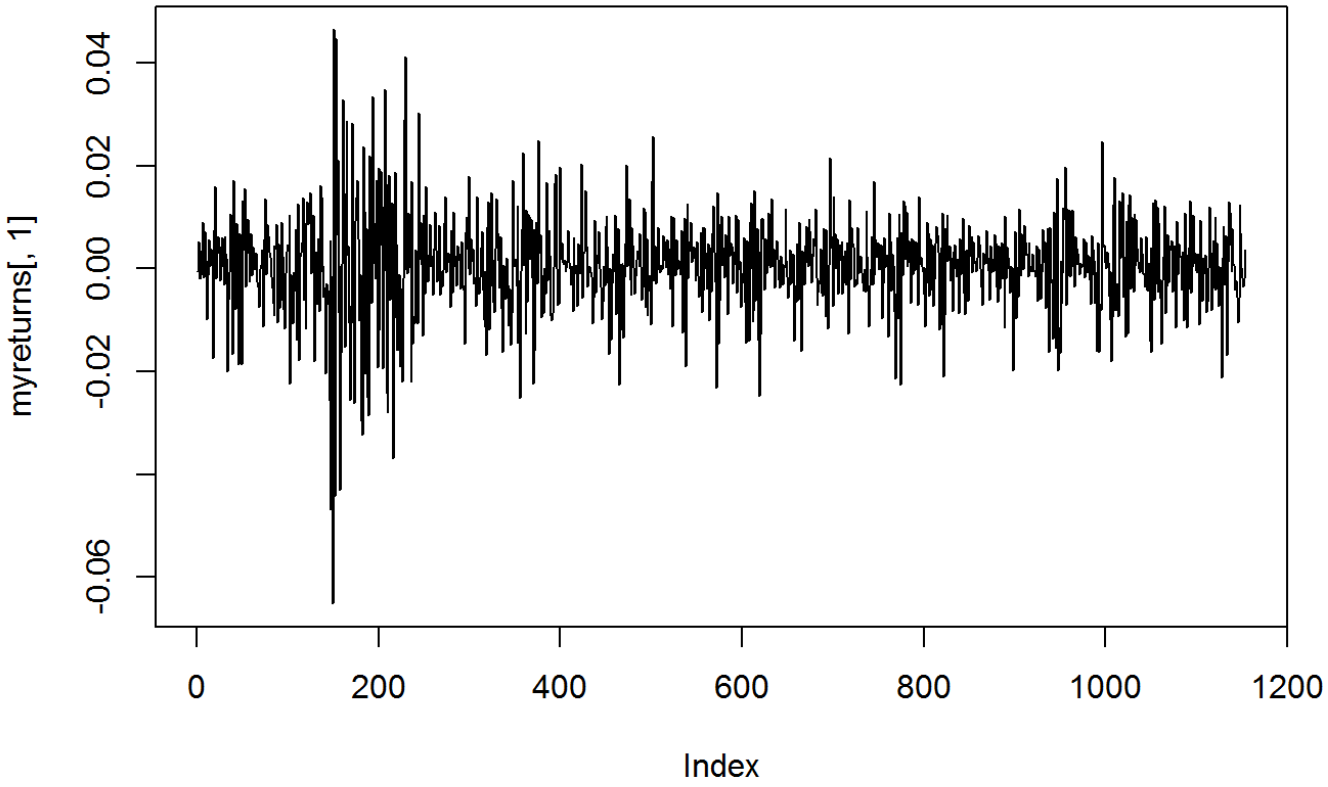
```
myreturns = YahooPricesToReturns(myprices)
```

View the returns as draws from the joint distribution

```
pairs(myreturns)
```




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



mu_SPY = mean(myreturns[,4]) sigma_SPY = sd(myreturns[,4])

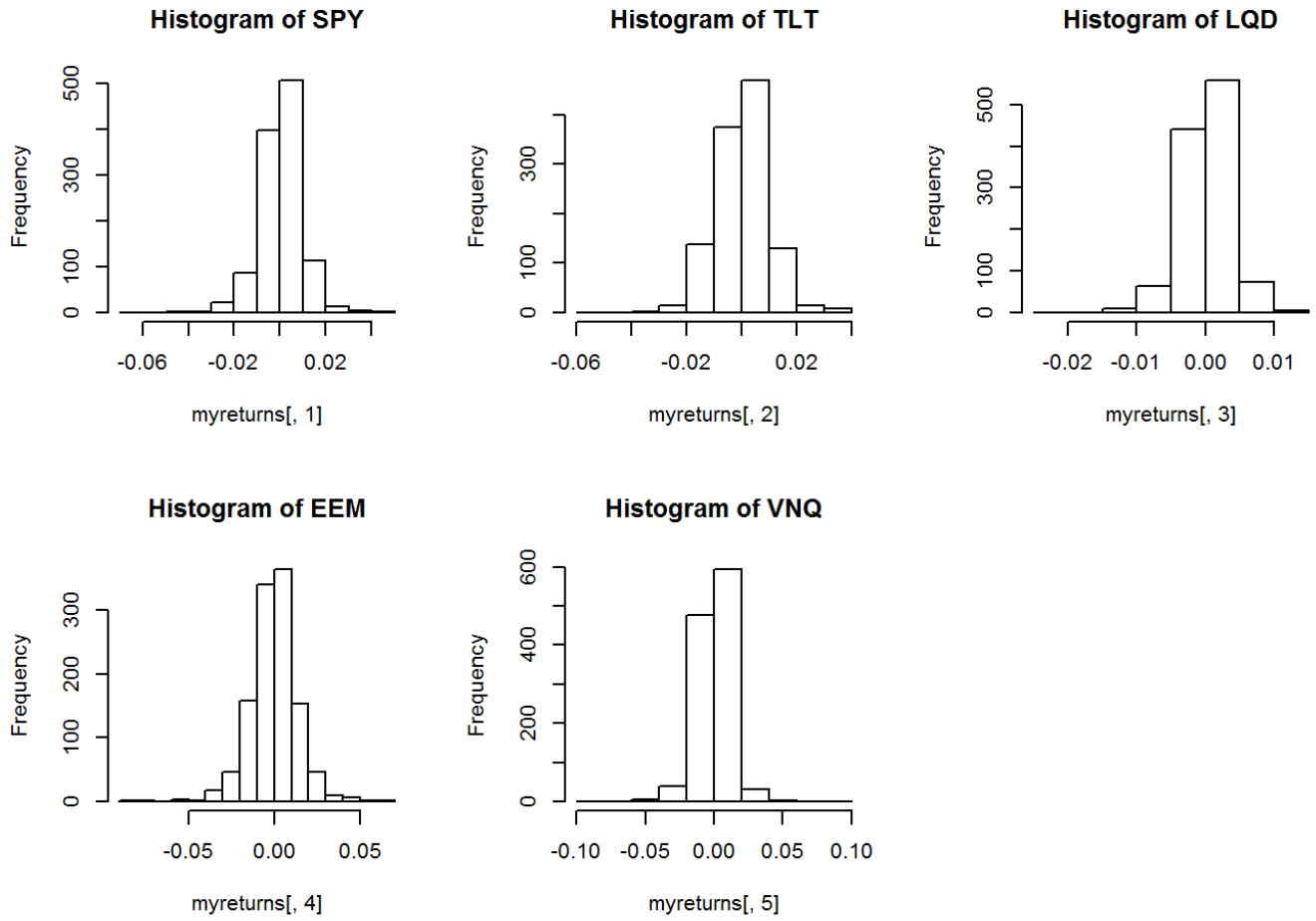
Calculate the standard deviation across different different stock returns

```
mynames = sapply(data.frame(myreturns), function(x) sd(x))
```

Compute the moments of a one-day change in your portfolio totalwealth = 100000 weights = c(0.20,0.20,0.20,0.20,0.20) # What percentage of your wealth will you put in each stock?

How much money do we have in each stock? holdings = weights * totalwealth

Plot for variability in returns for each stock over the period from='2011-01-01' to='2015-08-05'



Part(b)

After analysing the Standard Deviation of the risk/return properties of the 5 mentioned ETF's LQD and and SPY safe stocks to purchase since they have smaller standard deviations.

While EEM and VNQ are riskier stocks to purchase since they have higher standard deviations.

Below are the values of standard deviations for the 5 stocks mentioned. The standard deviation values helps in characterizing the risk/return properties for these stocks

```
mynames = sapply(data.frame(myreturns), function(x) sd(x))
mynames
```

```
## SPY.PctReturn TLT.PctReturn LQD.PctReturn EEM.PctReturn VNQ.PctReturn
##   0.009405747   0.009593108   0.003490087   0.013843982   0.011444111
```

Part(c)

Bootstrap resampling to estimate the 4-week (20 trading day) value at risk of each of your three portfolios.

(i) Equal Split Portfolio

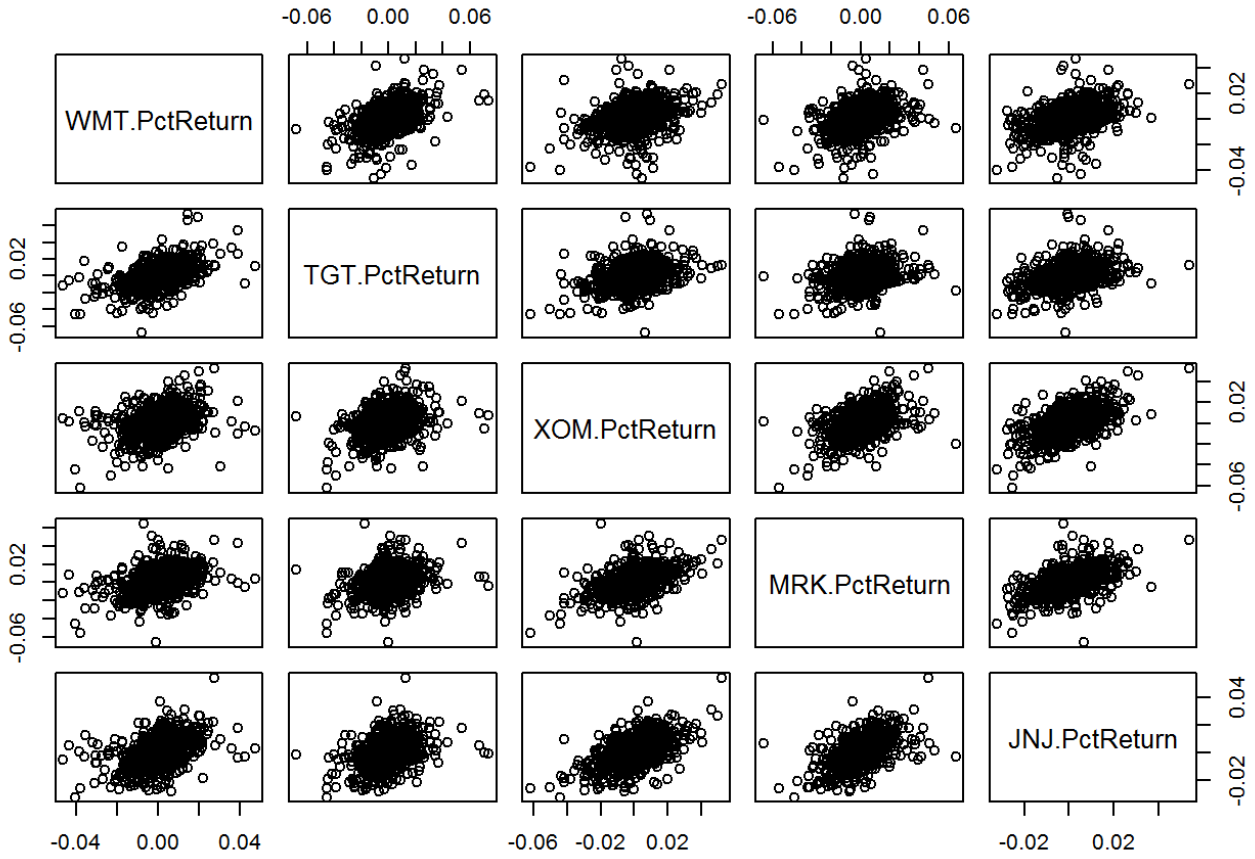
```
totalwealth = 100000
weights = c(0.20,0.20,0.20,0.20,0.20)
holdings = weights * totalwealth
n_days = 20
```

Using a bootstrap approach with more stocks

```
mystocks = c("WMT", "TGT", "XOM", "MRK", "JNJ")
myprices = yahooSeries(mystocks, from='2011-01-01', to='2015-07-30')
```

Compute the returns from the closing prices

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



Sample a random return from the empirical joint distribution This simulates a random day

```
return.today = resample(myreturns, 1, orig.ids=FALSE)
```

Update the value of your holdings and compute your new total wealth

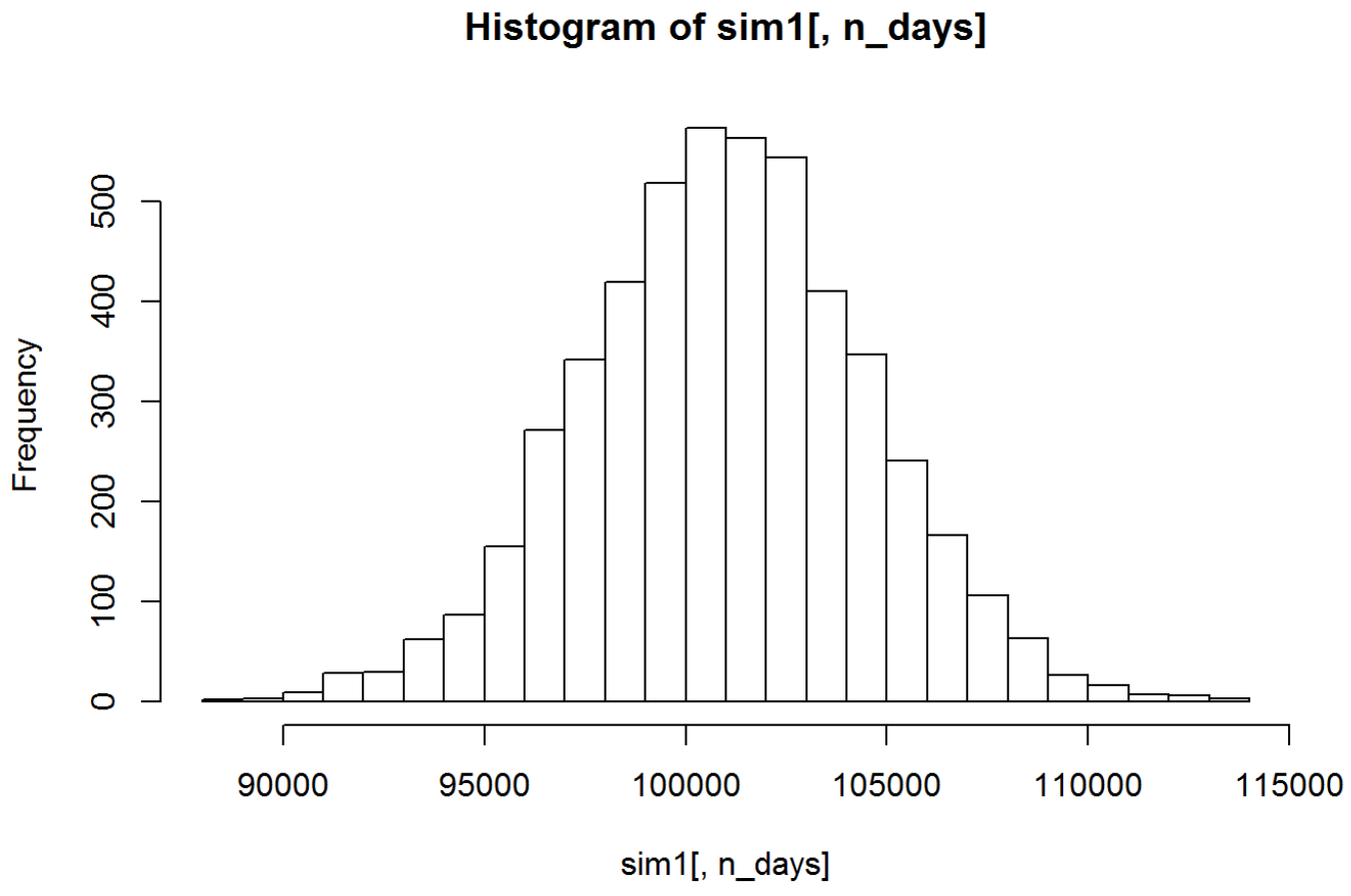
```
holdings = holdings + holdings*return.today
totalwealth = sum(holdings)
```

par(mfrow=c(3,1))

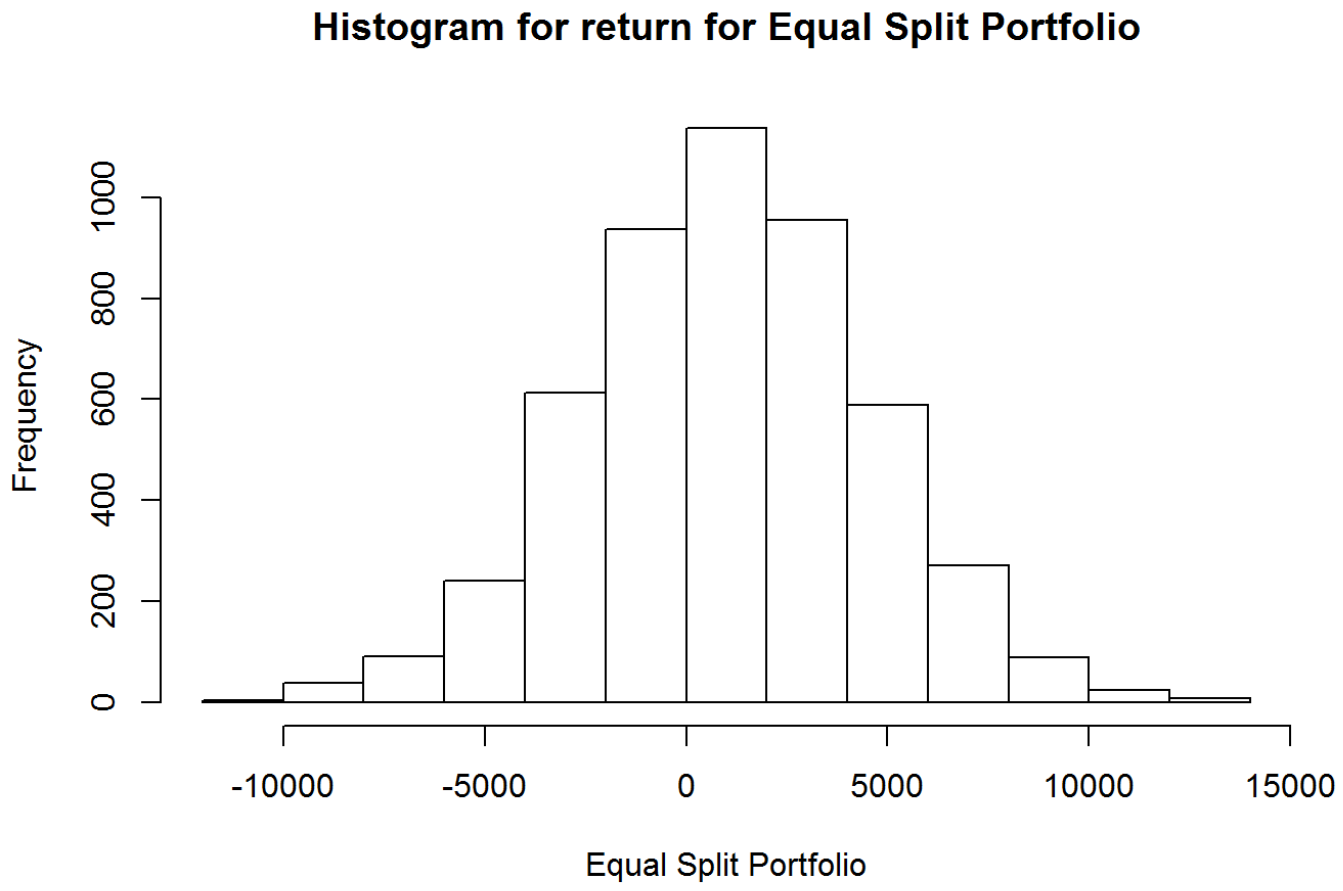
Bootstrapping for even split portfolio for a 20 day trading window

```
set.seed(40)
n_days = 20
# Now simulate many different possible trading years!
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(myreturns, 1, orig.ids=FALSE)
        holdings = holdings + holdings*return.today
        totalwealth = sum(holdings)
        wealthtracker[today] = totalwealth
    }
    wealthtracker
}

hist(sim1[,n_days], 20)
```




```
# Profit/loss
hist(sim1[,n_days]- 100000,xlab="Equal Split Portfolio",main="Histogram for return for
Equal Split Portfolio")
```




```
# Calculate 5% value at risk
quantile(sim1[,n_days], 0.05) - 100000
```

```
##        5%
## -4771.615
```

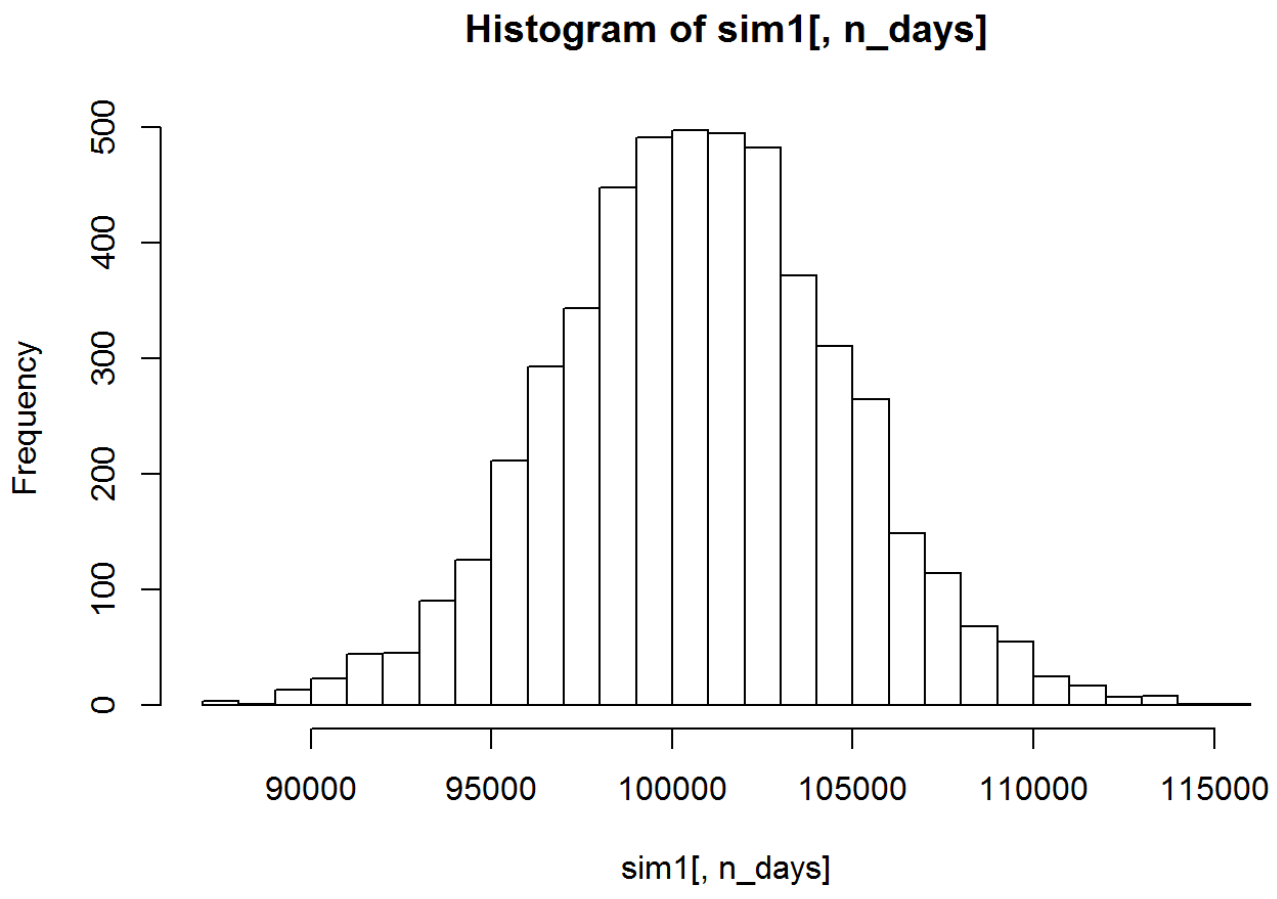
Analysis: The 5% risk associated with the portfolio (even split) is -3560.43

(ii) Safer Portfolio Bootstrapping for safer portfolio.Now loop over two trading weeks Considering the portfolio of SPY,TLT and LQD as a safe portfolio Going by the sd values of the above stocks, which is in the ratio of 2:2:1, we would invest in these stocks in the inverse proportion(lower the sd value, higher the investment in that stock,considering it's a safe portfolio) So the investment in this portfolio would be in the ratio of 1:1:2 for SPY,TLT and LQD resp.

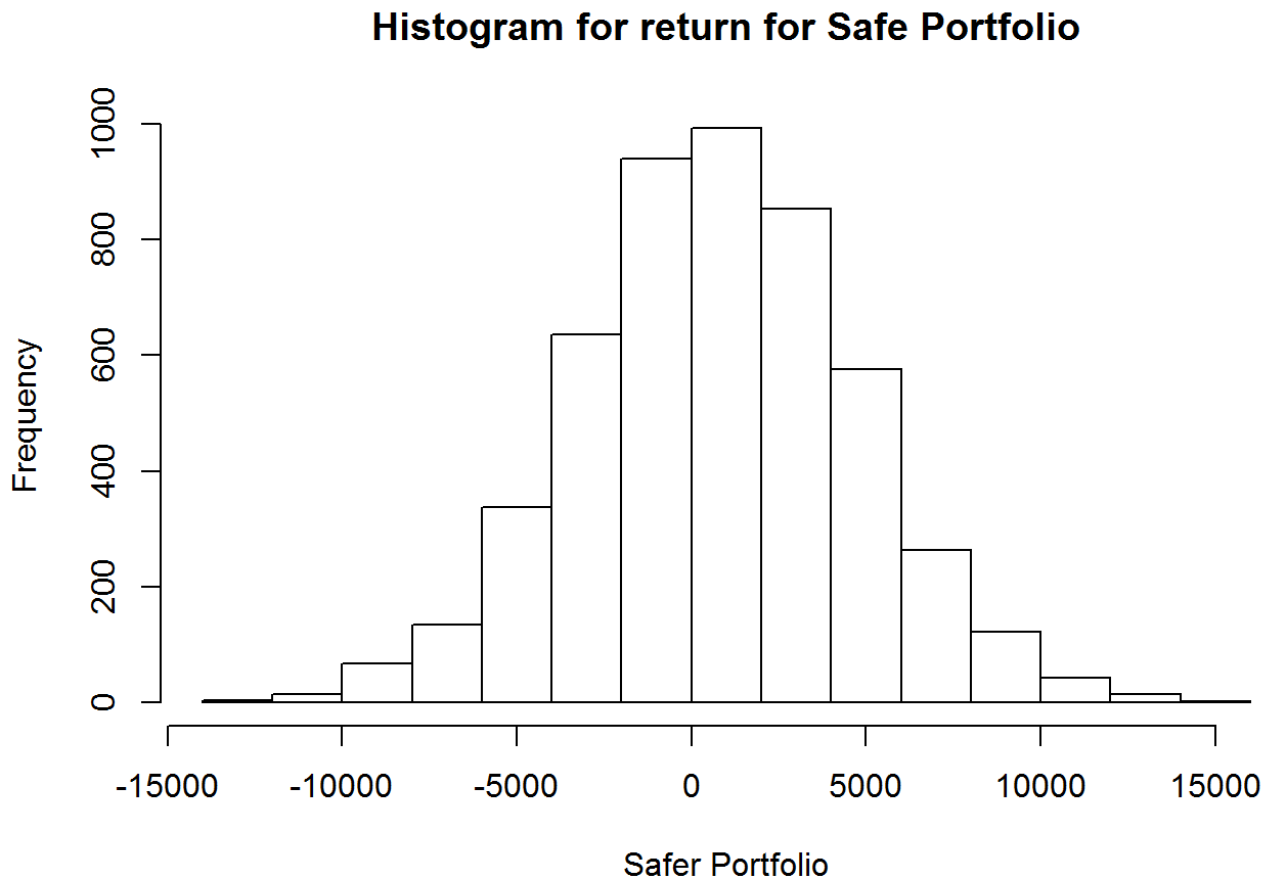
```
set.seed(40)
n_days = 20

## Now simulate many different possible trading years!
sim1 = foreach(i=1:5000, .combine='rbind') %do% {
    totalwealth = 100000
    weights = c(0.25, 0.25, 0.50,0,0)
    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(myreturns, 1, orig.ids=FALSE)
        holdings = holdings + holdings*return.today
        totalwealth = sum(holdings)
        wealthtracker[today] = totalwealth
    }
    wealthtracker
}

hist(sim1[,n_days], 20)
```




```
## Profit/loss
hist(sim1[,n_days]- 100000,xlab="Safer Portfolio",main="Histogram for return for Safe P
ortfolio")
```




```
## Calculate 5% value at risk
quantile(sim1[,n_days], 0.05) - 100000
```

```
##        5%
## -5716.463
```

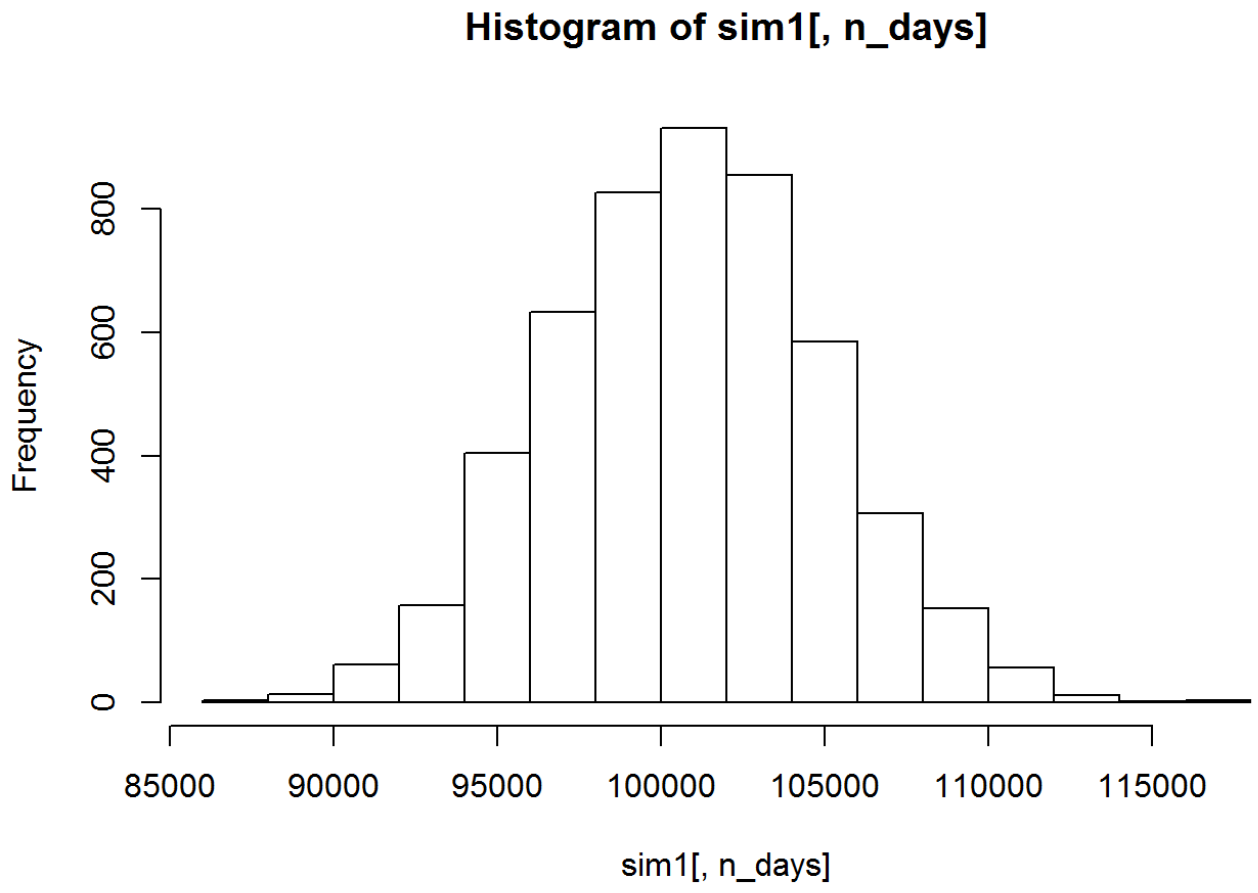
Analysis: The 5% risk associated with the portfolio (SPY,TLT and LQD) is -2217.123

(iii) Riskier Portfolio

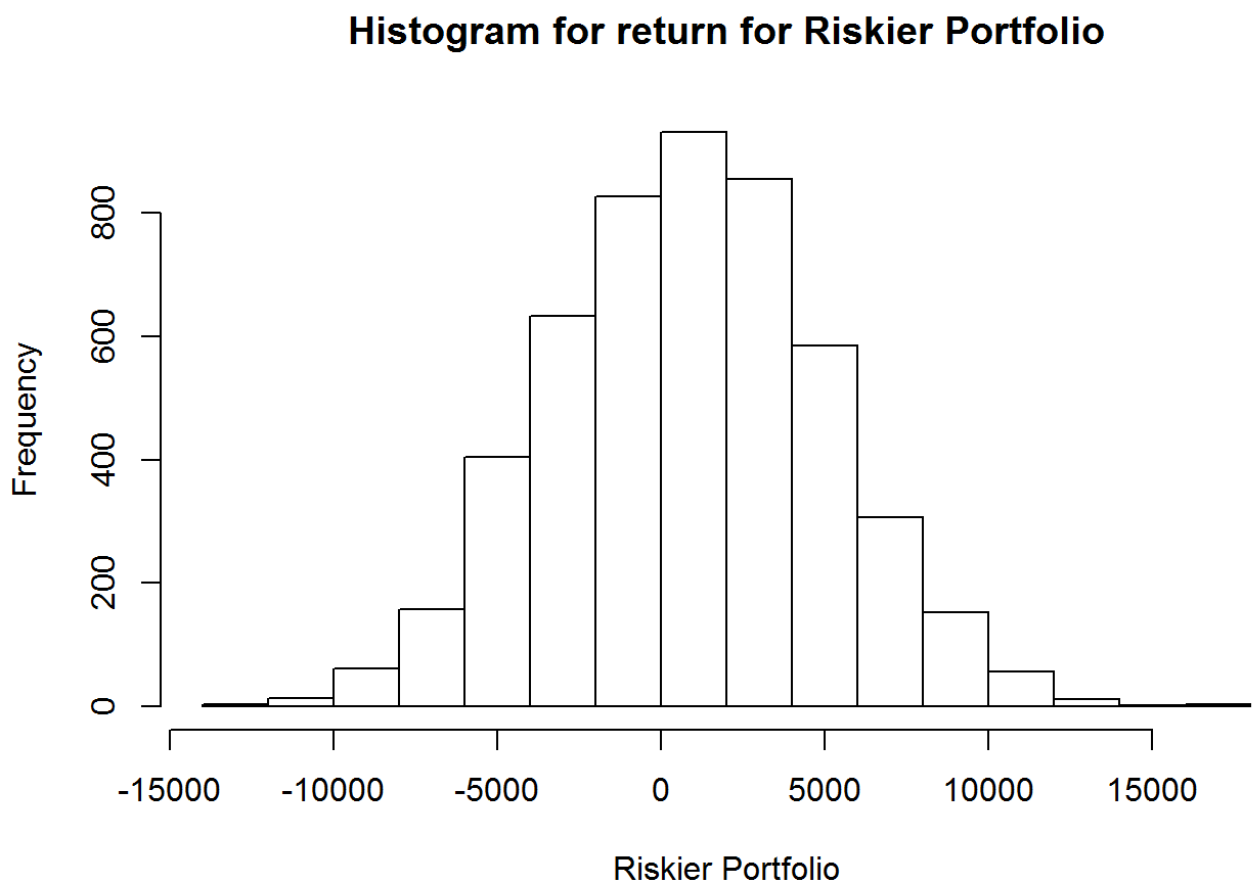
Bootstrapping for riskier portfolio.Now loop over two trading weeks Considering the portfolio of EEM and VNQ as a risky portfolio Going by the sd values of the above stocks, which is in the ratio of 6:5, we would invest in these stocks in the direct proportion(higher the sd value, higher the investment in that stock,considering it's a risky portfolio)

```
## Now simulate many different possible trading years!
set.seed(20)
n_days = 20
sim1 = foreach(i=1:5000, .combine='rbind') %do% {
    totalwealth = 100000
    weights = c(0.54, 0.46, 0,0,0)
    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(myreturns, 1, orig.ids=FALSE)
        holdings = holdings + holdings*return.today
        totalwealth = sum(holdings)
        wealthtracker[today] = totalwealth
    }
    wealthtracker
}

hist(sim1[,n_days], 20)
```




```
##Profit/loss
hist(sim1[,n_days]- 100000,xlab="Riskier Portfolio",main="Histogram for return for Risk
ier Portfolio")
```




```
## Calculate 5% value at risk
quantile(sim1[,n_days], 0.05) - 100000
```

```
##        5%
## -5889.972
```

Analysis:The 5% risk associated with the portfolio (EEM and VNQ) -5889.972

Ques 3 Clustering and PCA

Applying K-Means Clustering Technique for distinguishing between colors of wine

Reading the data

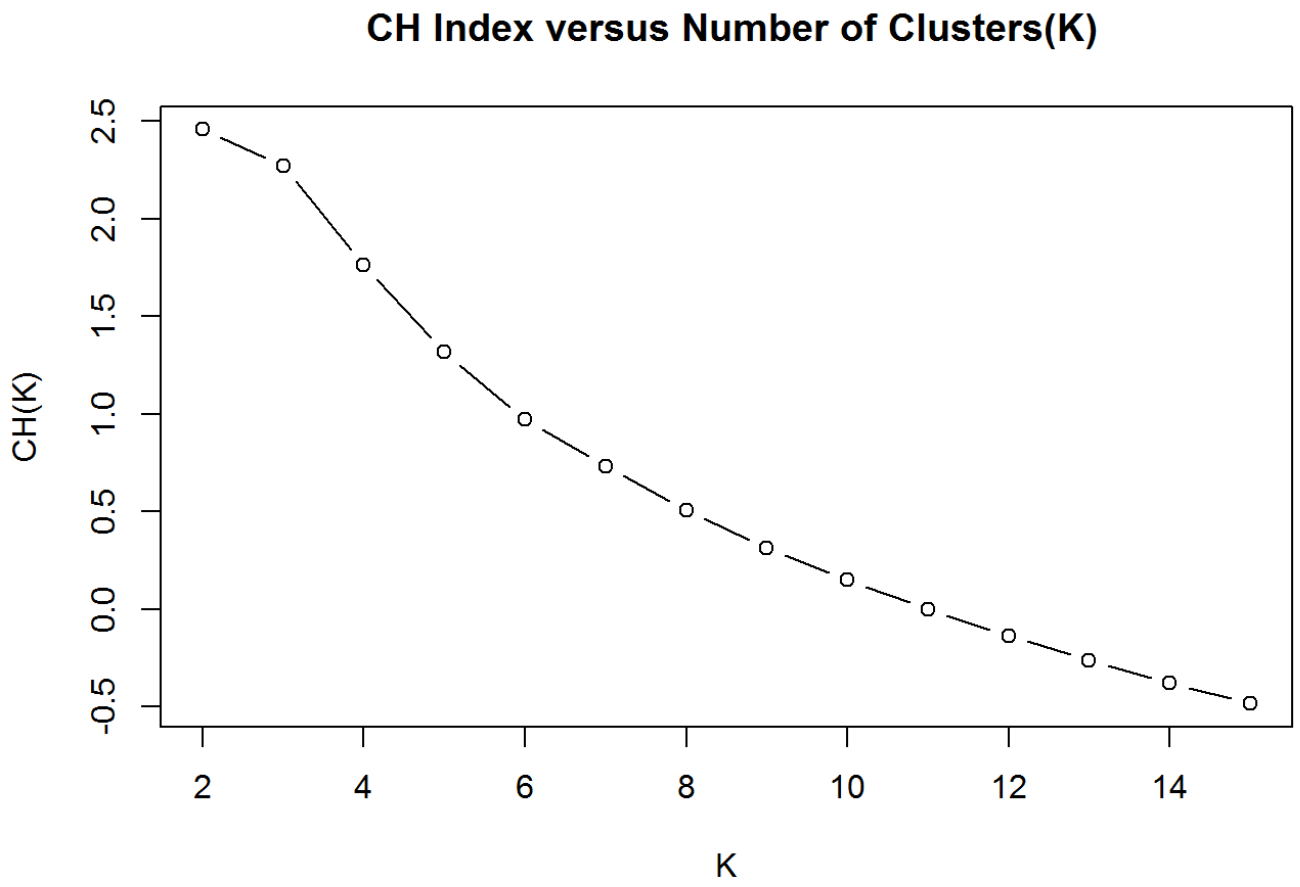
```
wine<-read.csv("F:/Predictive Modelling(JScott)/PredictiveModelling/STA380/wine.csv")
wine$quality<-as.factor(wine$quality)
wine_scaled <- scale(wine[,-c(12,13)], center=TRUE, scale=TRUE)
```

Transforming and scaling data

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

Finding the optimum value of number of clusters(k) using the value of CH- Index

```
n<-dim(wine_scaled)[2]
ch_index = numeric(length = 15)
for(i in 2:15){
  cluster_all = kmeans(wine_scaled, centers=i, nstart=20)
  ch_index[i-1] = (sum(cluster_all$betweenss)/(i-1))/(sum(cluster_all$withinss)/(n-i))
}
plot(2:15, ch_index[1:14], xlab='K', ylab='CH(K)', type='b', main=' CH Index versus Num
ber of Clusters(K)' )
```



Since there is a rise in the value at k=2 and a constant decline thereafter, value of k should be 2

Apply K-Means clustering for distinguishing between the 2 colors

```
set.seed(10)
clusterall <- kmeans(wine_scaled, centers=2, nstart=20)
```

Comparing the results of the clustering with the original clustered data on the basis of color

```
table(df_color,cluster_all$cluster)
```

```
##
## df_color   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15
##    red     8 291   4   2   0  34 422   8 538  24   4   4 256   1   3
##    white  91  22 690 568 526 501  15 438  12   0 598 605   2 591 239
```

Applying K-Means Clustering Technique for distinguishing amongst the 7 qualities of wine

```
cluster_all <- kmeans(wine_scaled, centers=7, nstart=50)
```

```
## Warning: did not converge in 10 iterations
```

```
df_quality=as.factor(wine$quality)
table(df_quality,cluster_all$cluster)
```

```
##
## df_quality   1   2   3   4   5   6   7
##          3   4   7   2   1   5   4   7
##          4  21  24  27   2  64  15  63
##          5  77 655 269  20 446 200 471
##          6 548 640 475   9 549 265 350
##          7 446 122 189   1 137 141  43
##          8  97  22  31   0  27  14   2
##          9   4   0   0   0   1   0   0
```

Analysis of K-Means technique for our problem: The technique was successful in distinguishing between the 2 colors while performed reasonably well while distinguishing amongst the qualities of wine

Using PCA to solve the problem

```
wine<-read.csv("F:/Predictive Modelling(JScott)/PredictiveModelling/STA380/wine.csv")
wine_scaled <- scale(wine[,-c(12,13)], center=TRUE, scale=TRUE)
```

** Applying PCA**

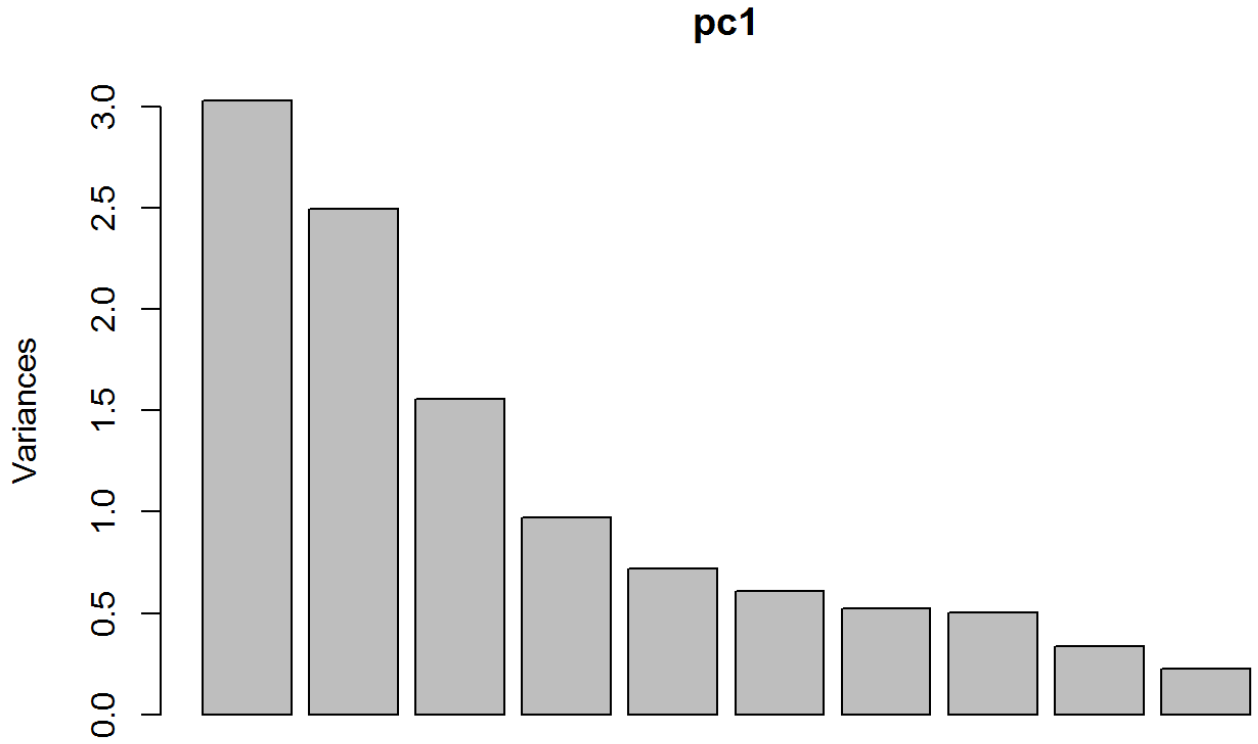
```
pc1 <-prcomp(wine_scaled)
```

Look at the basic plotting and summary methods

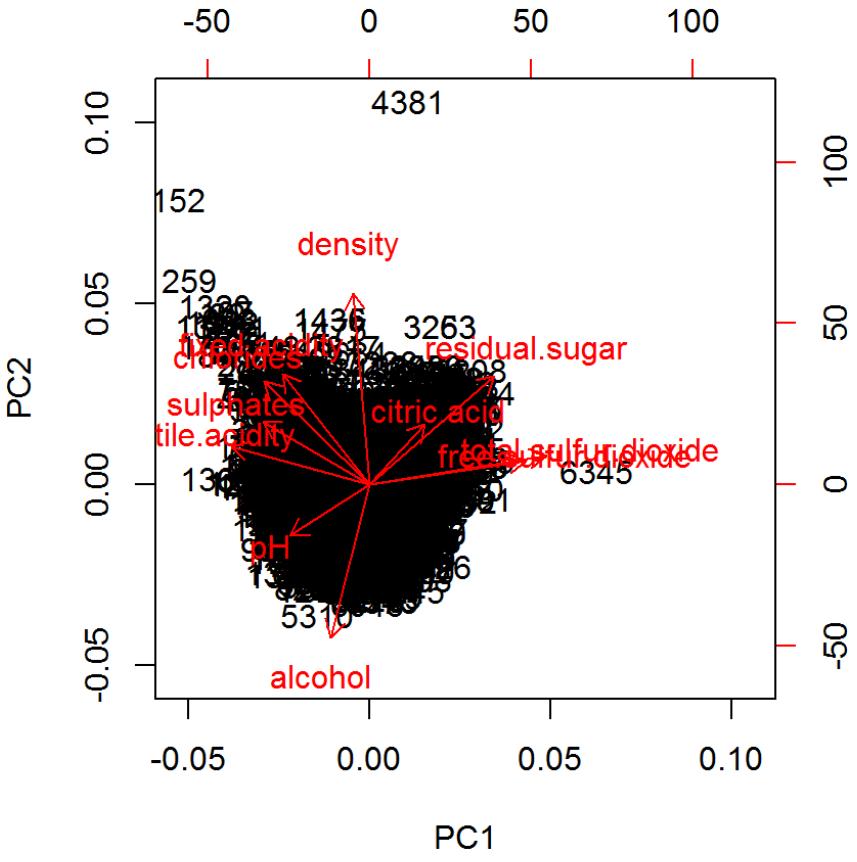
```
summary(pc1)
```

```
## 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
```

```
plot(pc1)
```


pc1
Variances
0.0
0.5
1.0
1.5
2.0
2.5
3.0

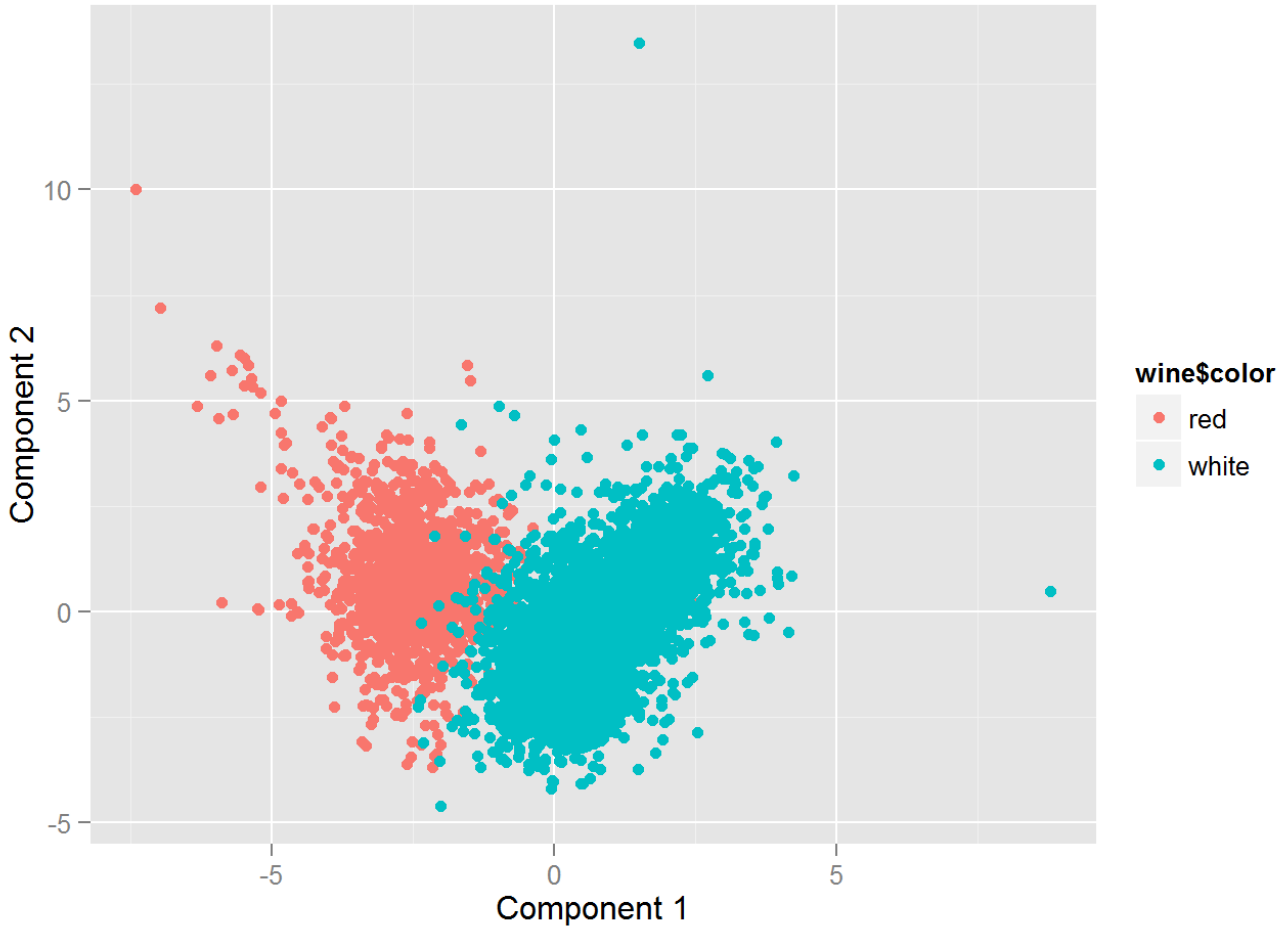
```
biplot(pc1)
```


-50
0
50
100
4381
152
259
density
3263
residual.sugar
citric.acid
sulphates
pH
alcohol
6345
0.10
0.05
0.00
-0.05
PC2
100
50
0
-50
-0.05
0.00
0.05
0.10
PC1

A more informative biplot for color and quality features

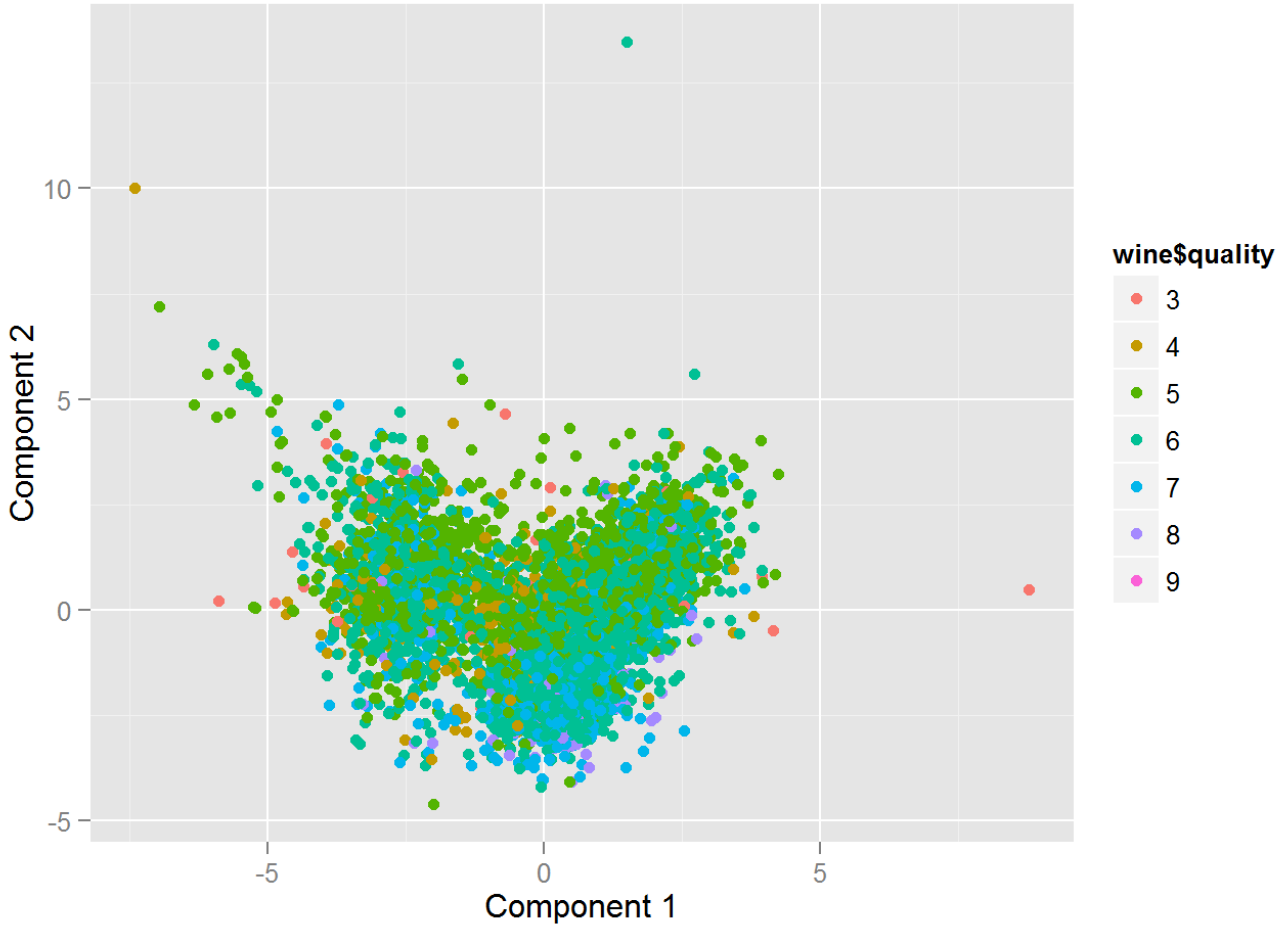
```
library(ggplot2)
loadings = pc1$rotation
scores = pc1$x

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




```
wine$quality<-as.factor(wine$quality)

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



Ques 4 Market segmentation

```
twitter_data<-read.csv("F:/Predictive Modelling(JScott)/PredictiveModelling/STA380/dat
a/social_marketing.csv")
twitter_data<-twitter_data[,-c(1,6)]
twitter_data_scaled <- scale(twitter_data, center=TRUE, scale=TRUE)
```

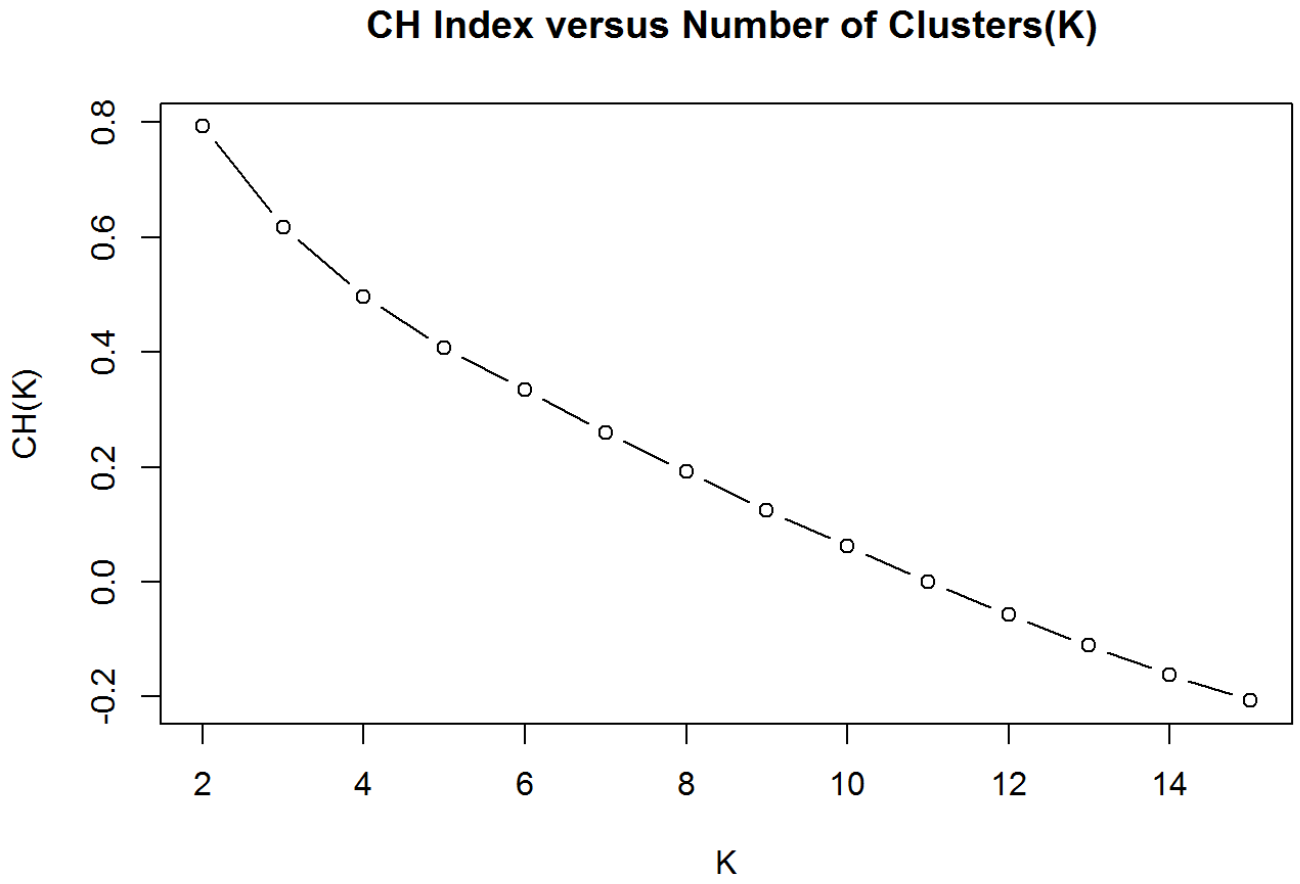
Finding the right number of clusters from CH Index value by analysing the graph

```
ch_index = numeric(length = 14)
for(i in 2:15){
  cluster_all = kmeans(twitter_data_scaled, centers=i, nstart=30)
  ch_index[i-1] = (sum(cluster_all$betweenss)/(i-1))/(sum(cluster_all$withinss)/(n-i))
}
```

```
## Warning: did not converge in 10 iterations
```

```
## Warning: did not converge in 10 iterations
```

```
plot(2:15, ch_index[1:14], xlab='K', ylab='CH(K)', type='b', main=' CH Index versus Num
ber of Clusters(K)' )
```



Run the K-Means clustering algorithm over the optimal number of clusters found above viz. 6

```
set.seed(10)
cluster_new <- kmeans(twitter_data, centers=6, nstart=20)
```

Get all the clusters sequentially and analyse each cluster to find which market segment is being represented by each of them. We do this, by first adding the cluster field to our original data frame and then calculating the mean over the values present under each column within each cluster.

```
twitter_data$cluster1<-cluster_new$cluster
```

Cluster 1: Studying this group,what we infer is that, this group is health conscious,cares about personal_fitness, health_nutrition,food,love outdoor activities and interacting with people.So mainly this group comprises of young men and women probably in the age group of 16-25 years

```
clust1= subset(twitter_data, cluster1==1)
tail(sort(sapply(clust1[,-36],mean)))
```

```
## health_nutrition           beauty          chatter          fashion
##         2.013487         3.845857         3.940270         5.689788
##    photo_sharing          cooking
##         5.899807        11.932563
```

Cluster 2: This group is religious,involved in parenting,cooking food,enjoys crafts,sports and chatting with people. So this group mainly comprises of people who are in the age group of 30-50 years.

```
clust1= subset(twitter_data, cluster1==2)
tail(sort(sapply(clust1[,-36],mean)))
```

```
##       politics  sports_fandom current_events       shopping  photo_sharing
##       1.461778       1.623245       1.865835       3.543682       5.617005
##        chatter
##       9.879875
```

Cluster 3: This group loves to travel,share photos,watches movies as well.This segment mainly consists of children and the youth population in the age group of 5-22 years.

```
clust1= subset(twitter_data, cluster1==3)
tail(sort(sapply(clust1[,-36],mean)))
```

```
## photo_sharing     computers       chatter          news        travel
##      2.267462      2.643952      4.044293      5.146508      6.347530
##      politics
##      9.870528
```

Cluster 4: This group loves to do shopping,has a taste in arts and keep themselves updated of all the latest events. The group probably comprises of mid-aged people in the age group of 30-55.

```
clust1= subset(twitter_data, cluster1==4)
tail(sort(sapply(clust1[,-36],mean)))
```

```
##    photo_sharing         outdoors          cooking          chatter
##         2.438384         2.438384         3.368687         4.022222
## personal_fitness health_nutrition
##         6.107071        12.275758
```

Cluster 5: This group has an interest in following politics and enjoying travelling as well.This segment of population mainly comprises of young men in the age group of 18-35 years.

```
clust1= subset(twitter_data, cluster1==5)
tail(sort(sapply(clust1[,-36],mean)))
```

```
##  sports_fandom sports_playing  photo_sharing        chatter  online_gaming
##       1.623153       2.487685       2.640394       4.071429      10.450739
##    college_uni
##      10.793103
```

Cluster 6: This group is active in businesses and chattering with new clients.This is a professional group of people. The working class population dominates this group.

```
clust1= subset(twitter_data, cluster1==6)
tail(sort(sapply(clust1[,-36],mean)))
```

```
##         travel           food current_events  photo_sharing  sports_fandom
##       1.115178       1.189605       1.378721       1.507077       1.517082
##        chatter
##       2.916301
```