STA 380 Homework 1: Barton, Jace

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To begin, I load the libraries I will need throughout my analysis.

```
library(dplyr)

## Warning: package 'dplyr' was built under R version 3.0.3

##
## 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

library(mosaic)

## Warning: package 'mosaic' was built under R version 3.0.3

## Loading required package: car

## Warning: package 'car' was built under R version 3.0.3

## Loading required package: lattice
## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 3.0.3

##
## Attaching package: 'mosaic'
##
## The following object is masked from 'package:car':
##
##     logit
##
## The following objects are masked from 'package:dplyr':
##
##     do, tally
##
## 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(ggplot2)
library(fImport)
```

```
## Warning: package 'fImport' was built under R version 3.0.3
```

```
## Loading required package: timeDate
```

```
## Warning: package 'timeDate' was built under R version 3.0.3
```

```
## Loading required package: timeSeries
```

```
## Warning: package 'timeSeries' was built under R version 3.0.3
```

```
library(foreach)
```

```
## Warning: package 'foreach' was built under R version 3.0.3
```

```
library(RCurl)
```

```
## Warning: package 'RCurl' was built under R version 3.0.3
```

```
## Loading required package: bitops
```

I will also be performing random draws. So the reader can reproduce my results, I will set the seed as value 722.

```
set.seed(722)
```

Now, to the analysis!

Exploratory Analysis

County Voting in Georgia for 2000 Election

To begin, I will import the data set, then view a summary of the data.

```
GeorgiaURLString =
getURL("https://raw.githubusercontent.com/jacebarton/STA380/master/data/georg
ia2000.csv", ssl.verifypeer=0L, followlocation = 1L)
Georgia = read.csv(text=GeorgiaURLString)
summary(Georgia)
```

```
##       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  
## 
```

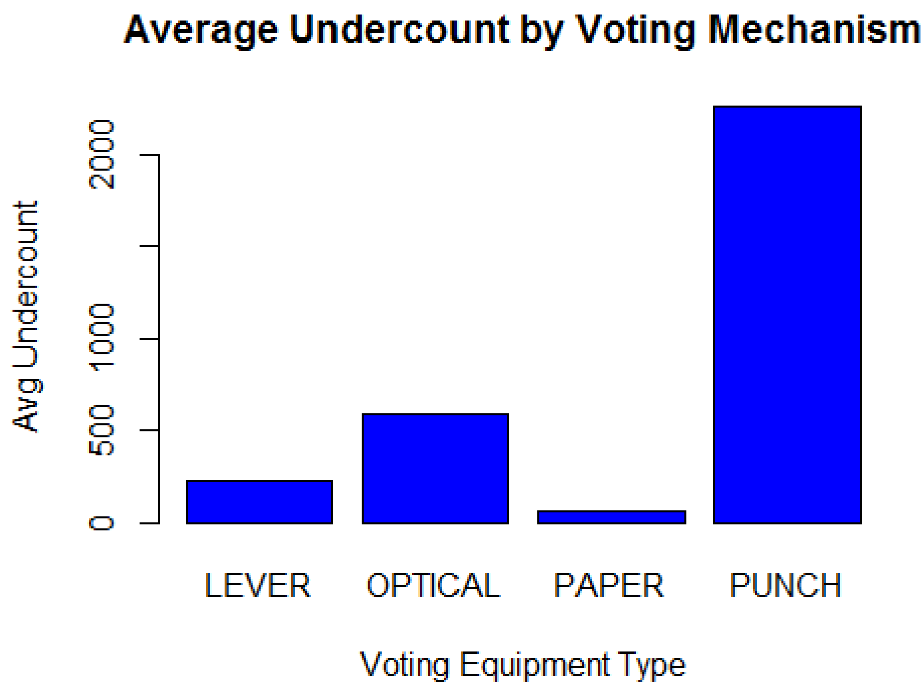
I now want to calculate the undercount for each county and append that to the dataframe. I then want to look at a pivot table of the undercount by machine type.

```
Georgia$undercount = abs(Georgia$votes - Georgia$ballots)
UndercountByEquip = group_by(Georgia, equip)
UndercountByEquip = summarise(UndercountByEquip, AvgUndercount = 
mean(Georgia$undercount), SumBallots = sum(Georgia$ballots), SumVotes = 
sum(Georgia$votes), BallotConversionRate = 
sum(Georgia$votes)/sum(Georgia$ballots))
UndercountByEquip
```

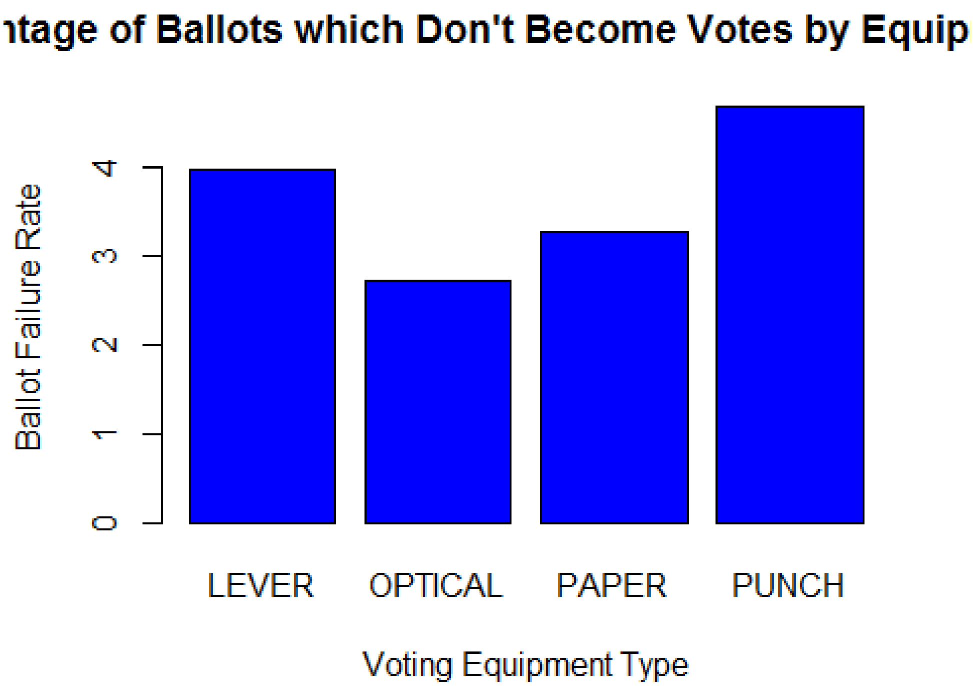
```
## Source: local data frame [4 x 5]
## 
##     equip AvgUndercount SumBallots SumVotes BallotConversionRate
## 1   LEVER      229.9459     427780   410764            0.9602225
## 2 OPTICAL      592.2727    1436159  1397069            0.9727816
## 3   PAPER       56.5000       3454     3341            0.9672843
## 4   PUNCH     2262.4706     823921   785459            0.9533183
```

It appears that the punch equipment type is vastly undercounting. It is the second most used equipment type, but has the lowest conversion rate of ballots to votes at 95%. I want to look at this information graphically though to confirm my suspicions.

```
barplot(UndercountByEquip$AvgUndercount, names = UndercountByEquip$equip, 
ylab="Avg Undercount", xlab="Voting Equipment Type", col=4, main="Average 
Undercount by Voting Mechanism")
```




```
barplot((1-UndercountByEquip$BallotConversionRate)*100, names =
UndercountByEquip$equip, ylab="Ballot Failure Rate", xlab="Voting Equipment
Type", col=4, main="Percentage of Ballots which Don't Become Votes by
Equipment Type")
```



The punch equipment is the biggest offender. But where are the punch machines located? Are they equally spread across Georgia? Or are they located in areas which are poorer? Or have a higher percentage of minorities?

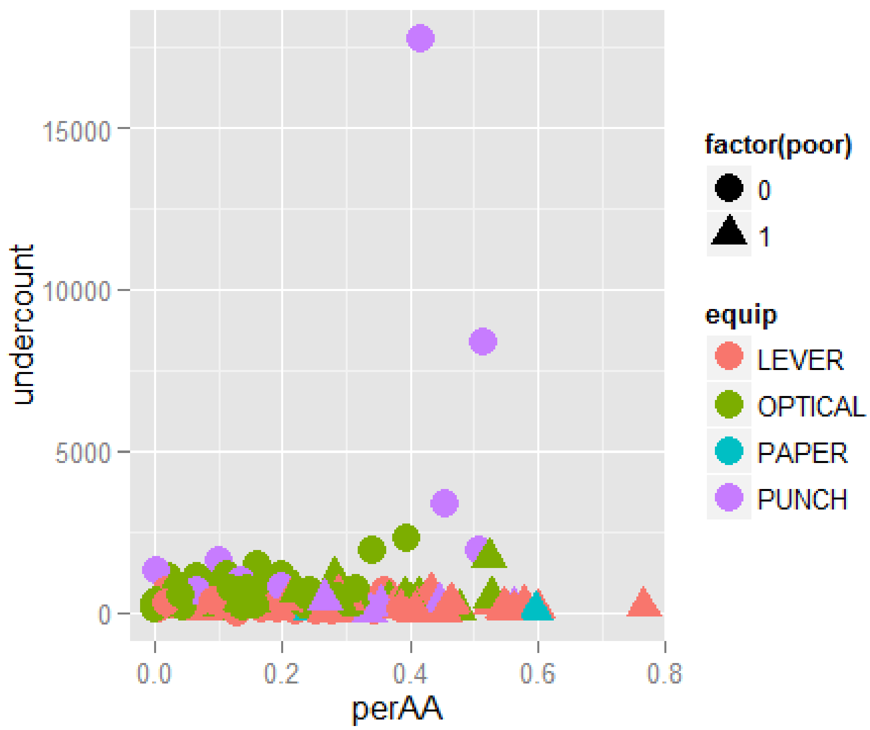
I begin by looking at a crosstab of county type (poor or rich) versus type of machine.

```
PoorVsEquip = xtabs(~poor + equip, data=Georgia)
PoorVsEquip

##     equip
## poor LEVER OPTICAL PAPER PUNCH
##    0    29      48     0    10
##    1    45      18     2     7

PoorVsEquipProp = prop.table(PoorVsEquip, margin=2)
PoorVsEquipProp

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

59% of punch machines were located in non-poor counties while 41% were located in poor counties. Thus, from this I can say non-poor counties were more likely to have their votes undercounted. But is that the full story?

The following plot graphs the percentage of the population in a county which is African American on the x-axis against the undercount in that county on the y-axis. The points are color coded to reflect the voting equipment used in the county. Finally, the poor counties are representing as triangles, while the non-poor counties are represented as octagons.

```
ggplot(Georgia, aes(x=perAA, y=undercount, color = equip, shape =
factor(poor))) + geom_point (size=5)
```



I immediately observe that the three counties with the most undercounted ballots were counties with a substantial African American population (greater than 40%). Those counties were also using punch cards. I also note that the right-most counties in the graph (the counties which are most substantially African-American in makeup) are poor.

In conclusion, punch machines see a higher rate of undercounting compared to other machine types. While the impact is spread between non-poor and poor counties about equally, minority counties are more likely to see substantial undercount than non-minority counties.

Bootstrapping

Stock market portfolios and levels of risk and return

The goal of this exercise is to see the levels of risk and return across varying compositions of different asset types. The asset types in question are domestic equities, Treasury bonds, corporate bonds, Emerging-market equities, and real estate. These five classes are represented in order by the following Exchange Traded Funds (ETFs). *SPY* TLT *LQD* EEM *VNQ

I first want to gather five years worth of returns on these five assets. This is accomplished below.

```
MyExchangeTradedFunds = c("SPY", "TLT", "LQD", "EEM", "VNQ")
ETFPrices = yahooSeries(MyExchangeTradedFunds, from='2010-08-01', to='2015-07-31')

summary(ETFPrices)

##     SPY.Open        SPY.High        SPY.Low        SPY.Close    
##  Min.   :104.9   Min.   :106.0   Min.   :104.3   Min.   :105.2  
##  1st Qu.:131.7   1st Qu.:132.5   1st Qu.:131.0   1st Qu.:131.8  
##  Median :149.9   Median :150.9   Median :149.5   Median :150.1  
##  Mean   :158.5   Mean   :159.3   Mean   :157.7   Mean   :158.5  
##  3rd Qu.:188.0   3rd Qu.:188.6   3rd Qu.:187.1   3rd Qu.:187.9  
##  Max.   :213.2   Max.   :213.8   Max.   :212.9   Max.   :213.5  
##    SPY.Volume         SPY.Adj.Close       TLT.Open         TLT.High     
##  Min.   : 42963400   Min.   : 95.03   Min.   : 88.69   Min.   : 89.14  
##  1st Qu.: 98758950   1st Qu.:121.34   1st Qu.:104.94   1st Qu.:105.54  
##  Median :131278200   Median :142.94   Median :115.25   Median :115.75  
##  Mean   :146760627   Mean   :151.67   Mean   :112.77   Mean   :113.33  
##  3rd Qu.:173130100   3rd Qu.:183.42   3rd Qu.:120.80   3rd Qu.:121.39  
##  Max.   :717828700   Max.   :212.62   Max.   :136.70   Max.   :138.50  
##     TLT.Low          TLT.Close        TLT.Volume       TLT.Adj.Close   
##  Min.   : 88.14   Min.   : 88.19   Min.   :  987200   Min.   : 77.11  
##  1st Qu.:104.48   1st Qu.:105.11   1st Qu.: 5867950   1st Qu.: 98.49  
##  Median :114.73   Median :115.29   Median : 7742500   Median :107.27  
##  Mean   :112.24   Mean   :112.79   Mean   : 8644372   Mean   :105.25  
##  3rd Qu.:120.29   3rd Qu.:120.84   3rd Qu.:10197050   3rd Qu.:114.67  
##  Max.   :136.66   Max.   :138.28   Max.   :46221000   Max.   :136.27  
##     LQD.Open        LQD.High        LQD.Low        LQD.Close    
##  Min.   :106.7   Min.   :107.3   Min.   :106.3   Min.   :106.8  
##  1st Qu.:112.7   1st Qu.:113.0   1st Qu.:112.4   1st Qu.:112.7  
##  Median :116.1   Median :116.3   Median :115.9   Median :116.2  
##  Mean   :115.9   Mean   :116.2   Mean   :115.7   Mean   :115.9  
##  3rd Qu.:119.4   3rd Qu.:119.6   3rd Qu.:119.2   3rd Qu.:119.4  
##  Max.   :123.5   Max.   :123.9   Max.   :123.4   Max.   :123.9  
##    LQD.Volume        LQD.Adj.Close       EEM.Open        EEM.High    
##  Min.   :  233400   Min.   : 89.53   Min.   :33.93   Min.   :34.94  
##  1st Qu.: 1054650   1st Qu.: 98.21   1st Qu.:39.88   1st Qu.:40.18  
##  Median : 1585400   Median :108.08   Median :41.79   Median :42.01  
##  Mean   : 1809465   Mean   :106.13   Mean   :42.10   Mean   :42.33  
##  3rd Qu.: 2241350   3rd Qu.:113.33   3rd Qu.:43.85   3rd Qu.:44.02  
##  Max.   :10863900   Max.   :121.63   Max.   :50.27   Max.   :50.43  
##     EEM.Low        EEM.Close       EEM.Volume         EEM.Adj.Close  
##  Min.   :33.42   Min.   :34.36   Min.   : 18409100   Min.   :31.74  
##  1st Qu.:39.62   1st Qu.:39.88   1st Qu.: 42995550   1st Qu.:38.24  
##  Median :41.52   Median :41.79   Median : 53611300   Median :40.01  
##  Mean   :41.83   Mean   :42.10   Mean   : 58088010   Mean   :39.94  
##  3rd Qu.:43.66   3rd Qu.:43.86   3rd Qu.: 68977100   3rd Qu.:41.82  
```

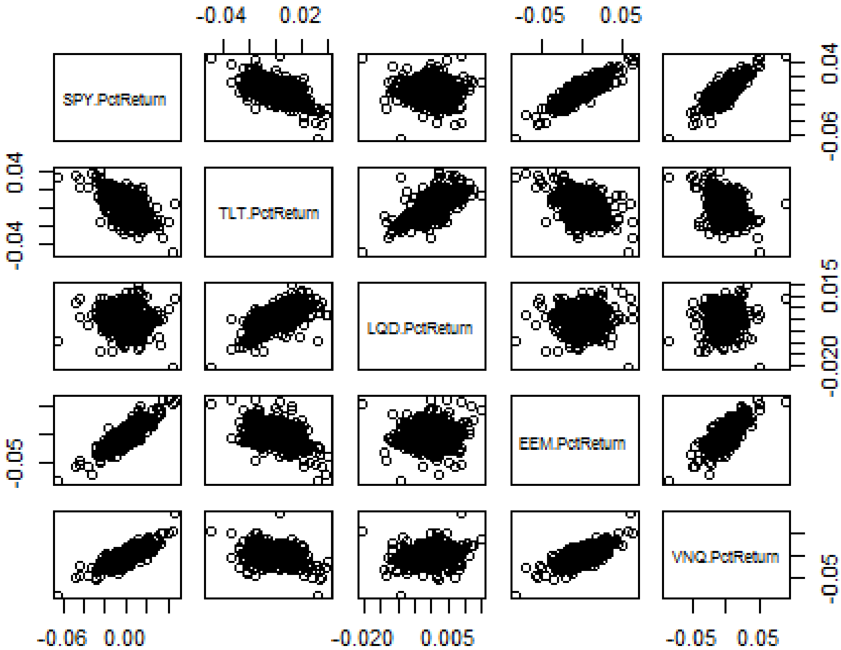
```
##  Max.   :49.94   Max.   :50.20   Max.   :191406700   Max.   :45.91
##     VNQ.Open         VNQ.High         VNQ.Low         VNQ.Close
##  Min.   :47.79   Min.   :49.34   Min.   :47.10   Min.   :48.47
##  1st Qu.:59.84   1st Qu.:60.26   1st Qu.:59.33   1st Qu.:59.97
##  Median :66.16   Median :66.51   Median :65.72   Median :66.20
##  Mean   :66.85   Mean   :67.27   Mean   :66.37   Mean   :66.84
##  3rd Qu.:73.85   3rd Qu.:74.30   3rd Qu.:73.50   3rd Qu.:73.88
##  Max.   :88.83   Max.   :89.27   Max.   :88.30   Max.   :88.65
##    VNQ.Volume        VNQ.Adj.Close
##  Min.   :  661100   Min.   :40.57
##  1st Qu.: 1839800   1st Qu.:51.33
##  Median : 2478900   Median :60.68
##  Mean   : 2849726   Mean   :61.20
##  3rd Qu.: 3410850   3rd Qu.:69.81
##  Max.   :11383300   Max.   :87.24
```

As seen, lots of information about the ETFs is returned by this data grab.However, for this theoretical exercise I am only interested in the returns of the assets. Below, I utilize a helper function presented in class by Dr. Scott to obtain the required 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))
}
```

I will now calculate the returns, look at the scatter plots of each return type against each other return type, and view summary statistics of the returns.

```
ETFReturns = YahooPricesToReturns(ETFPrices)
pairs(ETFReturns)
```




```
summary(ETFReturns)
```

```
##  SPY.PctReturn        TLT.PctReturn        LQD.PctReturn
##  Min.   :-0.0651232   Min.   :-0.0504495   Min.   :-0.0205232
##  1st Qu.:-0.0036944   1st Qu.:-0.0057510   1st Qu.:-0.0018105
##  Median : 0.0007426   Median : 0.0007862   Median : 0.0005005
##  Mean   : 0.0006210   Mean   : 0.0003404   Mean   : 0.0002036
##  3rd Qu.: 0.0053416   3rd Qu.: 0.0065291   3rd Qu.: 0.0022682
##  Max.   : 0.0464992   Max.   : 0.0396555   Max.   : 0.0146677
##  EEM.PctReturn        VNQ.PctReturn
##  Min.   :-8.337e-02   Min.   :-0.0868671
##  1st Qu.:-7.740e-03   1st Qu.:-0.0050551
##  Median : 4.649e-04   Median : 0.0009249
##  Mean   : 6.504e-05   Mean   : 0.0005391
##  3rd Qu.: 7.747e-03   3rd Qu.: 0.0066850
##  Max.   : 6.240e-02   Max.   : 0.0910393
```

What is the spread of these returns? I will look at the Standard Deviation (SD) and Interquartile Range (IQR) of each asset.

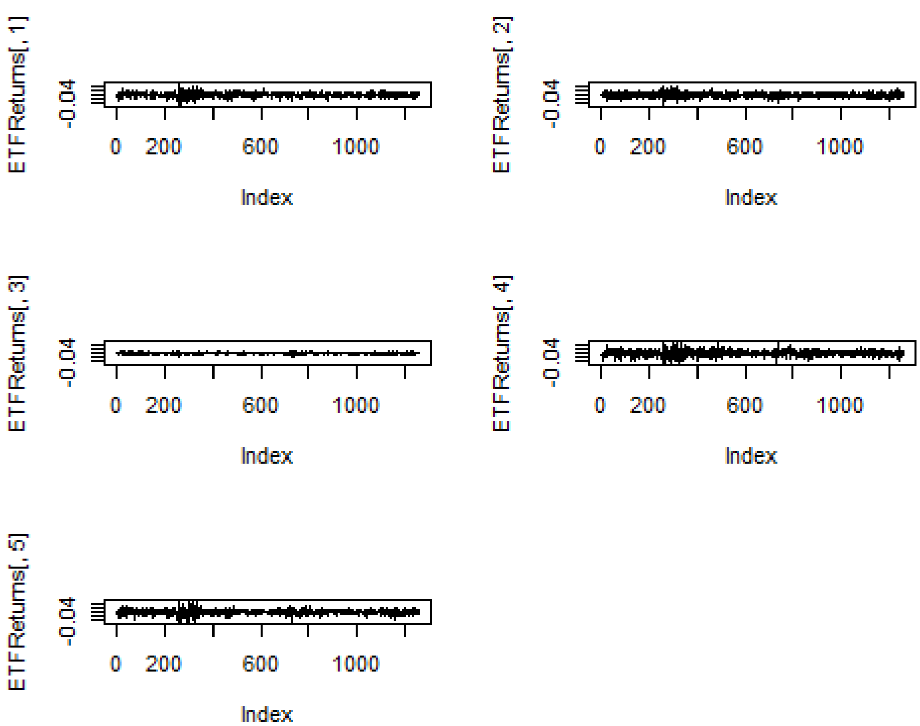
```
ReturnSDs = rep(0,5)

for (i in 1:length(ReturnSDs)){
  ReturnSDs[i] = sd(ETFReturns[,i])
}

ReturnIQRs = rep(0,5)
```

```
for (i in 1:length(ReturnIQRs)){
  ReturnIQRs[i] = quantile(ETFReturns[,i], .75) - quantile(ETFReturns[,i], 
.25)
}

ReturnSDs

## [1] 0.009351005 0.009768007 0.003581299 0.013727342 0.011520712

ReturnIQRs

## [1] 0.009035977 0.012280101 0.004078708 0.015486676 0.011740112
```

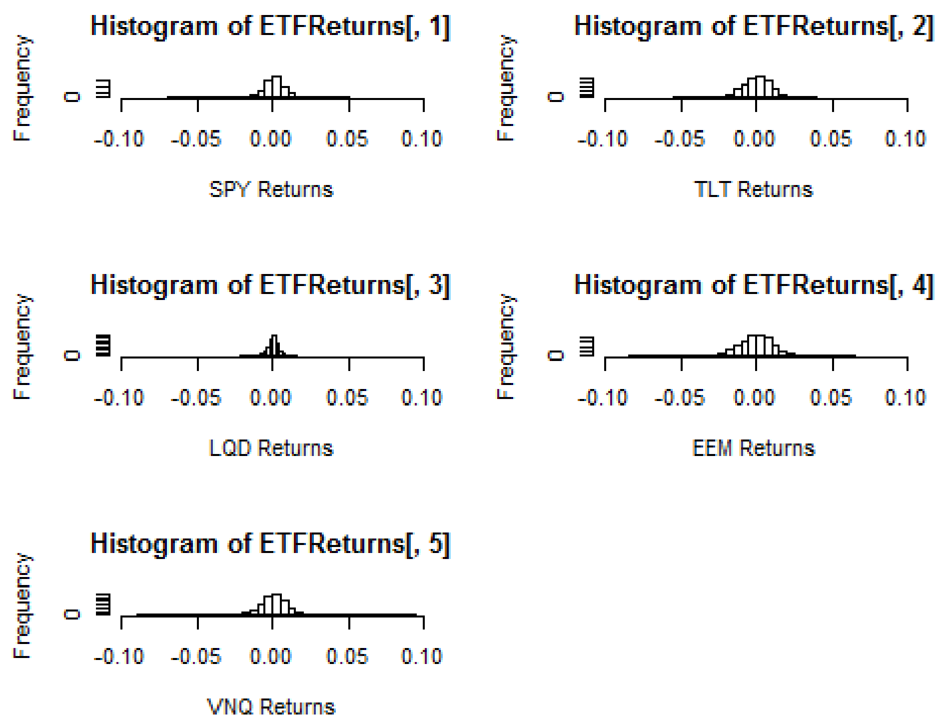
The results are similar. A standard deviation for each return type is about 1% (the exception being LQD) while the middle 50% of returns also varies by about 1%.

What do these returns look like as line graphs? As histograms?

```
par(mfrow=c(3,2))
plot(ETFReturns[,1], type='l', ylim=c(-.05, .05))
plot(ETFReturns[,2], type='l', ylim=c(-.05, .05))
plot(ETFReturns[,3], type='l', ylim=c(-.05, .05))
plot(ETFReturns[,4], type='l', ylim=c(-.05, .05))
plot(ETFReturns[,5], type='l', ylim=c(-.05, .05))

par(mfrow=c(3,2))
```



```r
hist(ETFReturns[,1], 25, xlim=c(-.10, .10), xlab="SPY Returns")
hist(ETFReturns[,2], 25, xlim=c(-.10, .10), xlab="TLT Returns")
hist(ETFReturns[,3], 25, xlim=c(-.10, .10), xlab="LQD Returns")
hist(ETFReturns[,4], 25, xlim=c(-.10, .10), xlab="EEM Returns")
hist(ETFReturns[,5], 50, xlim=c(-.10, .10), xlab="VNQ Returns")
```



While I will begin building my portfolios with an even split, eventually I will be interested in comprising risky and more reserved portfolios. Thus, looking at the volatility of each of the ETFs is informative. First off, I don't observe any seasonality or obvious trends in any of the returns. I do notice that the LQD returns are by far the least volatile, followed by the TLT returns. The SPY returns are closer to the EEM Returns and the VNQ returns, but they do offer a middle ground. The main difference is the latter two ETFs have more instances of extreme returns than the SPY asset. I will keep all of this in mind for when I am choosing which assets to include in my risky and risk-averse portfolios.

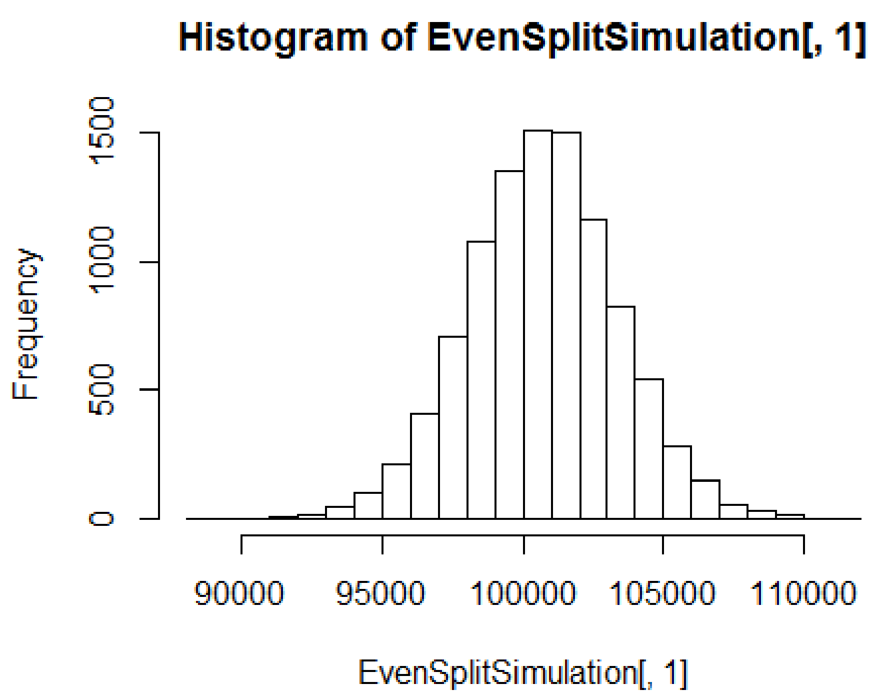
But first, I begin by selecting a portfolio that is an even split of all five assets. I want to get a sense of how well this portfolio would perform in an average month (here defined as 20 trading days) of performance. To do this, I will randomly select 20 days of returns (with replacement) from the five years of return data. I will start with $100,000. Rebalancing my money every day to maintain my desired 20-20-20-20-20 split, I will calculate how much money I possess at the end of the month. This will be one result. I will find 10,000 such results and average them together to get a sense of the true distribution of returns for this portfolio.

Below are the results for the Even Split Simulation.

```r
EvenSplitSimulation = foreach(i=1:10000, .combine='rbind') %do% {
  totalwealth = 100000
  weights = c(0.2, 0.2, 0.2, 0.2, 0.2)
  holdings = weights * totalwealth
  n_days = 20
  for(today in 1:n_days) {
    return.today = resample(ETFReturns, 1, orig.ids=FALSE)
    holdings = holdings + holdings*return.today
    totalwealth = sum(holdings)
    holdings = weights*totalwealth
  }
  totalwealth
}

summary(EvenSplitSimulation)
```

```
##        V1
##  Min.   : 88718
##  1st Qu.: 98945
##  Median :100718
##  Mean   :100712
##  3rd Qu.:102459
##  Max.   :111523
```

```r
par(mfrow=c(1,1))
hist(EvenSplitSimulation[,1], 25)
```



```r
sd(EvenSplitSimulation)

## [1] 2665.102
```

In terms of expected return, the center of the even split distribution is about $700. I can expect a standard deviation of about $2700. Maximum and minimum losses are both at about $11,000.

I now want to set up a vector to keep track of the alpha values across each of my simulations. The alpha value of a simulation will tell me what return I can expect at the 5th percentile.

```r
AlphaLevels = rep(0,3)
AlphaLevels[1] = quantile(EvenSplitSimulation,0.05) - 100000
AlphaLevels[1]

## [1] -3645.636
```

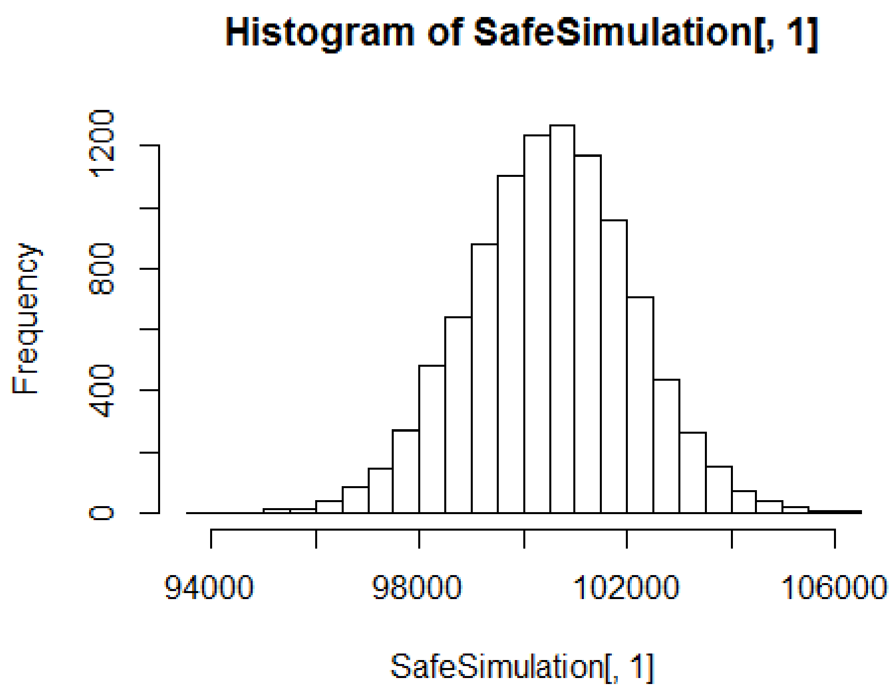
Thus, in 95% of cases, I will do better than a loss of $3600.

I now move on to finding a safer portfolio - one with less spread. From earlier, I remember that by far the least variable asset was LQD. I want the large majority of my portfolio to be in this stock. I will also include the next two least variable assests, TLT and SPY, though in smaller proportions. I arbitrarily choose to put 80% of my portfolio in LQD with 10% each in TLT and SPY. I keep the same parameters as before of 20 days and $100,000 starting value with rebalancing at the end of each day.

```r
set.seed(722)
SafeSimulation = foreach(i=1:10000, .combine='rbind') %do% {
  totalwealth = 100000
  weights = c(0.1, 0.1, 0.8)
  holdings = weights * totalwealth
  n_days = 20
  wealthtracker = rep(0, n_days) # Set up a placeholder to track total wealth
  for(today in 1:n_days) {
    return.today = resample(ETFReturns[,c(1,2,3)], 1, orig.ids=FALSE)
    holdings = holdings + holdings*return.today
    totalwealth = sum(holdings)
    wealthtracker[today] = totalwealth
    holdings = weights*totalwealth
  }
  totalwealth
}

summary(SafeSimulation)

##        V1
##  Min.   : 93692
##  1st Qu.: 99463
##  Median :100534
##  Mean   :100513
```

```
##   3rd Qu.:101561
##   Max.   :106498
```

```r
par(mfrow=c(1,1))
hist(SafeSimulation[,1], 25)
```




```r
sd(SafeSimulation)
```

```
## [1] 1583.293
```

```r
AlphaLevels[2] = quantile(SafeSimulation,0.05) - 100000
AlphaLevels[2]
```

```
## [1] -2120.949
```

We achieve a much lower standard deviation of about $1600. My minimum loss is about $6000 and my maximum gain is about $6000 as well. My average return is about $500. In 95% of cases, I can expect to do better than a loss of $2100.

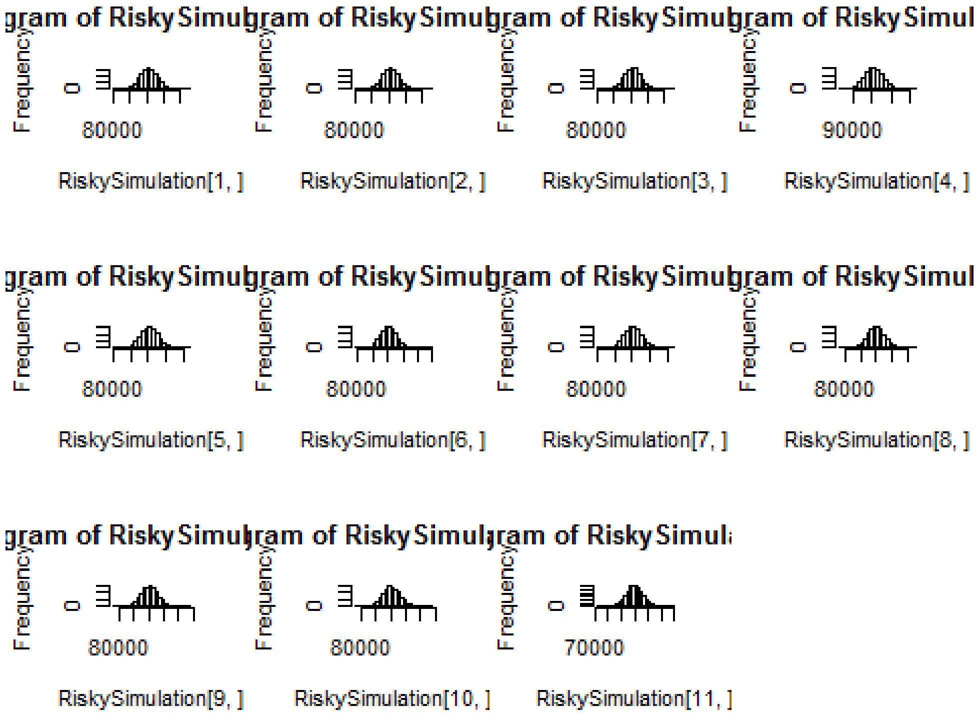
Finally, I want to evaluate a risky portfolio. I earlier noted that the two most variable assets of the five were EEM and VNQ. I will thus be building my portfolio around these two assets. However, I want to be more systematic in choosing how I weight the two ETFs. Thus, I will run the risky simulation 11 times, starting with 100% of my money in VNQ and working my way in 10% increments to having all of my money in EEM. For example, in the third run, 80% of my money will be in VNQ and 20% in EEM.

```r
set.seed(722)
PossibleWeights = seq(0, 1, length = 11)
```

```r
ReturnValues = rep(0, 10000)
RiskySimulation = foreach(i=1:11, .combine = 'rbind') %do% {
  for(j in 1:10000) {
    totalwealth = 100000
    weights = c(PossibleWeights[i], 1-PossibleWeights[i])
    holdings = weights * totalwealth
    n_days = 20
    wealthtracker = rep(0, n_days) # Set up a placeholder to track total
wealth
    for(today in 1:n_days) {
      return.today = resample(ETFReturns[,c(4,5)], 1, orig.ids=FALSE)
      holdings = holdings + holdings*return.today
      totalwealth = sum(holdings)
      wealthtracker[today] = totalwealth
      holdings = weights*totalwealth
    }
    ReturnValues[j] = totalwealth
  }
  ReturnValues
}
```

But which set of weights do I choose to be my "risky" portfolio? First, let's look at what the histograms of returns look like.

```r
par(mfrow=c(3, 4))
hist(RiskySimulation[1,], 25)
hist(RiskySimulation[2,], 25)
hist(RiskySimulation[3,], 25)
hist(RiskySimulation[4,], 25)
hist(RiskySimulation[5,], 25)
hist(RiskySimulation[6,], 25)
hist(RiskySimulation[7,], 25)
hist(RiskySimulation[8,], 25)
hist(RiskySimulation[9,], 25)
hist(RiskySimulation[10,], 25)
hist(RiskySimulation[11,], 25)
```

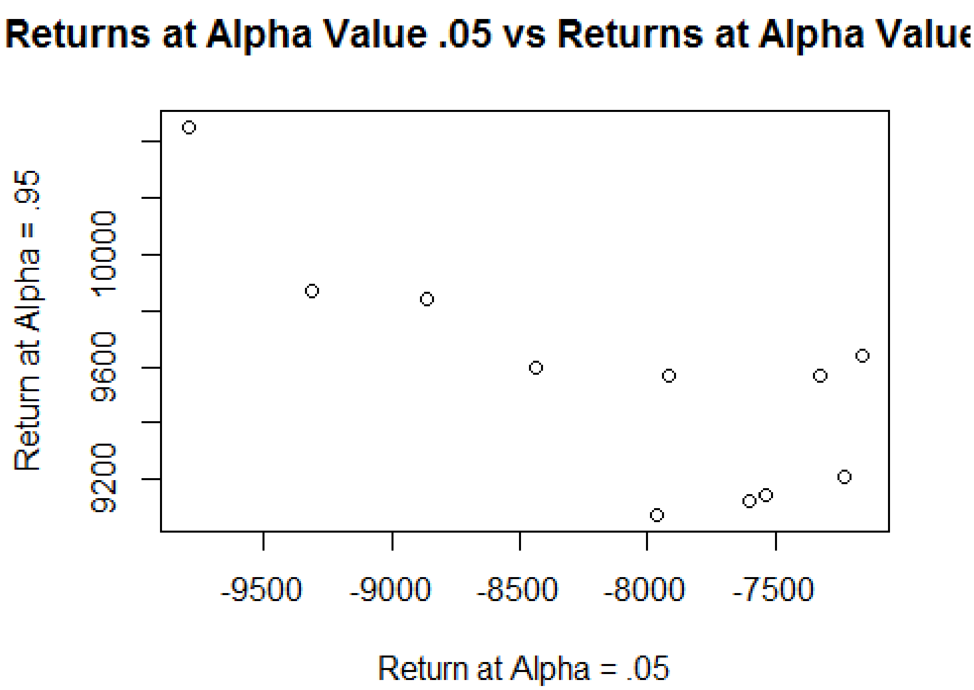


It's hard to see much difference here. Perhaps the alpha levels will be revealing. I will plot my return at alpha = .05 for each portfolio against that same portfolio's return at alpha = .95.

```
AlphaVsOneMinusAlpha = matrix(0, nrow=11, ncol=2)

for (i in 1:length(AlphaVsOneMinusAlpha[,1])) {
  AlphaVsOneMinusAlpha[i,1] = quantile(RiskySimulation[i,],0.05) - 100000
}

for (i in 1:length(AlphaVsOneMinusAlpha[,2])) {
  AlphaVsOneMinusAlpha[i,2] = quantile(RiskySimulation[i,],0.95) - 100000
}

AlphaVsOneMinusAlpha

##            [,1]     [,2]
##  [1,] -7323.255 9570.039
##  [2,] -7159.853 9641.565
##  [3,] -7227.039 9205.495
##  [4,] -7537.103 9139.401
##  [5,] -7600.073 9124.357
##  [6,] -7962.509 9071.581
##  [7,] -7919.841 9565.188
##  [8,] -8438.530 9599.067
##  [9,] -8860.268 9843.345
```

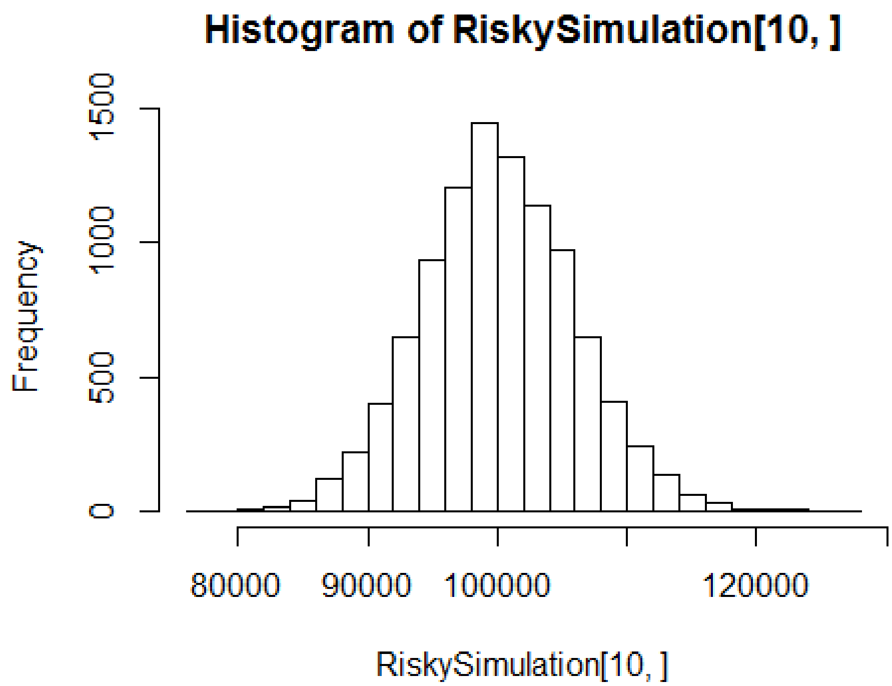
```
## [10,] -9310.423  9868.803
## [11,] -9797.346 10453.997
```

```
par(mfrow=c(1, 1))
plot(AlphaVsOneMinusAlpha, main="Returns at Alpha Value .05 vs Returns at
Alpha Value .95", xlab="Return at Alpha = .05", ylab = "Return at Alpha =
.95")
```



It thus looks like the "riskiest" portfolio is portfolio 11, which has 100% of the money in EEM. Since this violates the spirit of having a portfolio comprised of two assets, I will instead choose portfolio 10, which has the next lowest return at alpha = .05. Here is the summary of Portfolio 10, which is 90% EEM and 10% VNQ.

```
summary(RiskySimulation[10,])

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   77430   96230   99960  100100  104000  126300

par(mfrow=c(1,1))
hist(RiskySimulation[10,], 25)
```




```
sd(RiskySimulation[10,])

## [1] 5853.336
```

We achieve a much higher standard deviation of about $5850. My minimum loss is about $23,000 and my maximum gain is about $26,000. My average return is about $100, though my median return is to lose $40. In 95% of cases, I can expect to do better than a loss of $9300.

I now need to update my alpha vector to include the risky portfolio.

```
AlphaLevels[3] = quantile(RiskySimulation[10,],0.05) - 100000

AlphaLevels

## [1] -3645.636 -2120.949 -9310.423
```

Which portfolio I recommend depends entirely upon the riskiness of the indivdual investor. Personally as a risk-averse individual, I would opt for the "safe" portfolio, but I know I'm not going to have the chance to make 20% returns with this portfolio - the absolute best case scenario is 6% and the most likely is 0.5%. The even-split portfolio represents a nice middle ground between the two extremes of risk. My best case scenario bumps up to a 10% gain with a most likely return of about 0.7%. The risky portfolio is too volatile for my money. The standard deviation is around double that of the even split portfolio. I know there is risk inherent in the stock market, but the risky portfolio seems too much like gambling for my taste.

Clustering and PCA

Characteristics of Wine from Northern Portugal

Given only chemical properties, can I distinguish whether a wine is red or white? More challenging, can I distinguish the quality of the wine from its chemical characteristics?

I begin my analysis by loading in the data.

```
WineURLString =
getURL("https://raw.githubusercontent.com/jacebarton/STA380/master/data/wine.
csv", ssl.verifypeer=0L, followlocation = 1L)
Wine = read.csv(text=WineURLString)
summary(Wine)
```

```
##  fixed.acidity    volatile.acidity  citric.acid     residual.sugar
##  Min.   : 3.800   Min.   :0.0800   Min.   :0.0000   Min.   : 0.600
##  1st Qu.: 6.400   1st Qu.:0.2300   1st Qu.:0.2500   1st Qu.: 1.800
##  Median : 7.000   Median :0.2900   Median :0.3100   Median : 3.000
##  Mean   : 7.215   Mean   :0.3397   Mean   :0.3186   Mean   : 5.443
##  3rd Qu.: 7.700   3rd Qu.:0.4000   3rd Qu.:0.3900   3rd Qu.: 8.100
##  Max.   :15.900   Max.   :1.5800   Max.   :1.6600   Max.   :65.800
##    chlorides        free.sulfur.dioxide total.sulfur.dioxide
##  Min.   :0.00900   Min.   :  1.00      Min.   :  6.0
##  1st Qu.:0.03800   1st Qu.: 17.00      1st Qu.: 77.0
##  Median :0.04700   Median : 29.00      Median :118.0
##  Mean   :0.05603   Mean   : 30.53      Mean   :115.7
##  3rd Qu.:0.06500   3rd Qu.: 41.00      3rd Qu.:156.0
##  Max.   :0.61100   Max.   :289.00      Max.   :440.0
##     density             pH          sulphates         alcohol
##  Min.   :0.9871   Min.   :2.720   Min.   :0.2200   Min.   : 8.00
##  1st Qu.:0.9923   1st Qu.:3.110   1st Qu.:0.4300   1st Qu.: 9.50
##  Median :0.9949   Median :3.210   Median :0.5100   Median :10.30
##  Mean   :0.9947   Mean   :3.219   Mean   :0.5313   Mean   :10.49
##  3rd Qu.:0.9970   3rd Qu.:3.320   3rd Qu.:0.6000   3rd Qu.:11.30
##  Max.   :1.0390   Max.   :4.010   Max.   :2.0000   Max.   :14.90
##     quality        color
##  Min.   :3.000   red  :1599
##  1st Qu.:5.000   white:4898
##  Median :6.000
##  Mean   :5.818
##  3rd Qu.:6.000
##  Max.   :9.000
```

There are 1600 red wines and 4900 white wines represented in the data. The quality of all the wines ranges from 3-9 on a 1-10 scale with an average of about 6.

Clustering

In order to perform clustering analysis, I will need to scale and center this wine data. In this process, I will also remove the quality and color features as these are outputs I will eventually attempt to predict. I will keep track of the means and standard deviations of each feature in case I want to convert back to unstandardized data.

```
WineScaled = scale(Wine[,-(c(12,13))], center=TRUE, scale=TRUE)

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

In class, we discussed both hierarchical clustering and K-means clustering. For this data set, I know I'm not going to want many clusters as ultimately I'm going to be interested in predicting only a handful of output classes (Red vs Wine and a number from 3-9 for color and quality, respectively). With only a few clusters, hierarchical clustering is not an ideal candidate as I will get the overwhelming majority of the data points in one cluster and then several much smaller clusters. Thus, I will pursue K-Means clustering.

But how many K's shall I choose? To answer this, I will use the CH(k) matrix we discussed in class which attempts to balance inter-cluster distance with intra-cluster distance. To calculate CH(k), I will loop through K values from 2 to 20 looking for the maximum CH(k).

```
PossibleKs = matrix(0, nrow=19, ncol=2)
PossibleKs[,1] = 2:20

set.seed(722)
for(i in 1:19){
  WineKMeanClusters = kmeans(WineScaled, i, nstart=50)
  CHk = ((WineKMeanClusters$betweenss/(i-
1))/(WineKMeanClusters$tot.withinss/(nrow(WineScaled)-i)))
  PossibleKs[i,2] = CHk
}

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: Quick-TRANSfer stage steps exceeded maximum (= 324850)

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

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

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

## Warning: did not converge in 10 iterations

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## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

plot(PossibleKs, xlab="# of Clusters", Ylab="CH(k)", main="Choosing K to
Maximize CH(k)")

## Warning in plot.window(...): "Ylab" is not a graphical parameter

## Warning in plot.xy(xy, type, ...): "Ylab" is not a graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "Ylab" is not
## a graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "Ylab" is not
## a graphical parameter

## Warning in box(...): "Ylab" is not a graphical parameter

## Warning in title(...): "Ylab" is not a graphical parameter
```
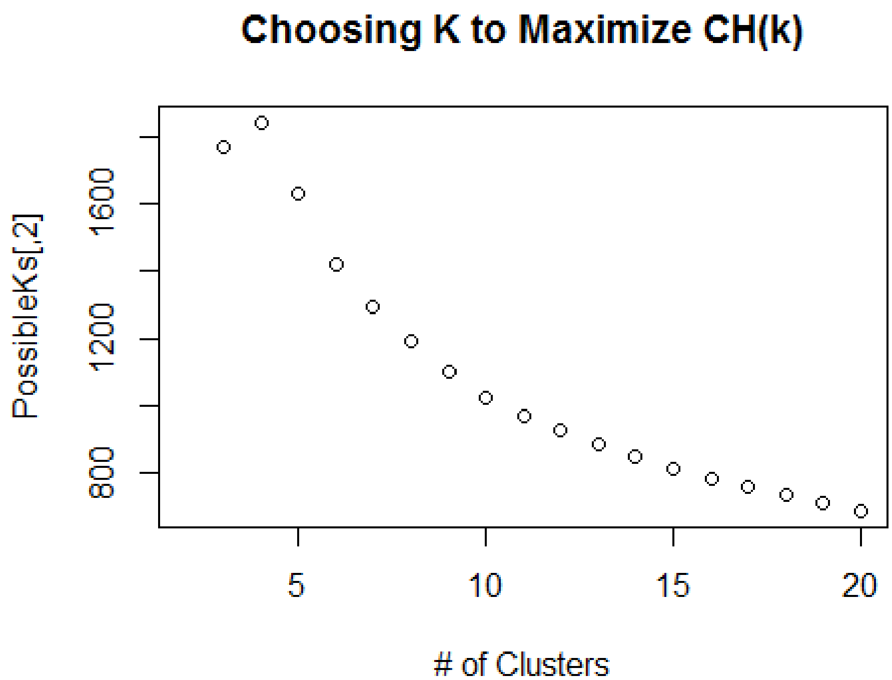



CH(k) peaks at k=4, so I will have four clusters of wine.

I now will add which cluster each wine is assigned to on the original data set.

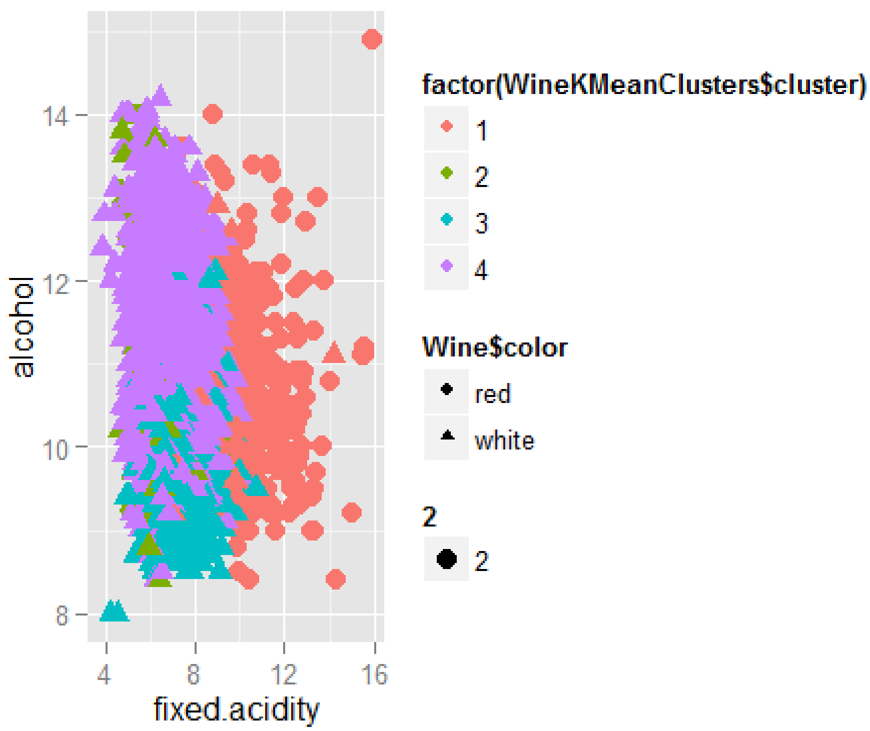
```
set.seed(722)
WineKMeanClusters = kmeans(WineScaled, 4, nstart=50)
Wine$cluster = factor(WineKMeanClusters$cluster)
WineKMeanClusters$centers

##   fixed.acidity volatile.acidity citric.acid residual.sugar  chlorides
## 1     1.9272263        0.4658003  0.97461378     -0.5621815  1.2651916
## 2     0.0310115        1.6264134 -1.24743592     -0.6171303  0.6338616
## 3    -0.1946570       -0.3568490  0.26831468      1.2164487 -0.1039414
## 4    -0.3381025       -0.4400768  0.02868768     -0.4336995 -0.4480556
##   free.sulfur.dioxide total.sulfur.dioxide    density          pH
## 1         -0.88068209          -1.21063354  0.9263596 -0.09894986
## 2         -0.77099529          -1.10241627  0.4510104  0.96385049
## 3          0.85498261           0.96137057  0.7633800 -0.38505854
## 4         -0.07507221           0.04818817 -0.8602004 -0.06191271
##    sulphates     alcohol
## 1  1.3525304  0.02318728
## 2  0.3994917 -0.21910641
## 3 -0.2580984 -0.79520297
## 4 -0.2894397  0.57819988

summary(factor(WineKMeanClusters$cluster))
```

```
##    1    2    3    4
##  687 1007 1873 2930
```

Cluster 4 is the biggest, followed by Clusters 3, 2, and 1 in descending order. Clusters 1 and 2 have high acidity, while cluster 4 has the highest alcohol level and cluster three the most sugar. Note that the centers are given in Z-scores since this analysis was run on the centered and scaled data.

Below, two sample plots are shown. The X and Y axis in each plot are different features of the wine. The wine cluster is indicated by color while the wine color is indicated by shape. These plots are only meant to get a sense of how well we can judge the clusters, though since we can only visualize two dimensions at a time, this sense will be dulled.

```r
qplot(fixed.acidity, alcohol, data = Wine,
color=factor(WineKMeanClusters$cluster), shape=Wine$color, size=2)
```




```r
qplot(chlorides, citric.acid, data = Wine,
color=factor(WineKMeanClusters$cluster), shape=Wine$color, size=2)
```

Most importantly, how well do my clusters differentiate between wine colors?

```
ClusterVsColor = xtabs(~cluster + color, data=Wine)
ClusterVsColor

##         color
## cluster  red white
##       1  638    49
##       2  917    90
##       3    4  1869
##       4   40  2890

ClusterVsColorProp = prop.table(ClusterVsColor, margin=1)
ClusterVsColorProp

##         color
## cluster         red       white
##       1 0.928675400 0.071324600
##       2 0.910625621 0.089374379
##       3 0.002135611 0.997864389
##       4 0.013651877 0.986348123
```

Clusters 3 and 4 are the "White" clusters, and they perform best with a 99% classification rate. Clusters 1 and 2 are the "red" clusters, and they don't perform quite as well, but both still ahve classifcation rates above 90%.

How well can the clusters judge quality compared to the baseline percentages?

```r
ClusterVsQuality = xtabs(~cluster + quality, data=Wine)
ClusterVsQuality
```

```
##        quality
## cluster    3    4    5    6    7    8    9
##       1    5   20  229  285  136   12    0
##       2    7   71  503  367   53    6    0
##       3   10   44  797  833  157   31    1
##       4    8   81  609 1351  733  144    4
```

```r
ClusterVsQualityProp = prop.table(ClusterVsQuality, margin=1)
ClusterVsQualityProp
```

```
##        quality
## cluster            3            4            5            6            7
##       1 0.0072780204 0.0291120815 0.3333333333 0.4148471616 0.1979621543
##       2 0.0069513406 0.0705064548 0.4995034757 0.3644488580 0.0526315789
##       3 0.0053390283 0.0234917245 0.4255205553 0.4447410571 0.0838227443
##       4 0.0027303754 0.0276450512 0.2078498294 0.4610921502 0.2501706485
##        quality
## cluster            8            9
##       1 0.0174672489 0.0000000000
##       2 0.0059582920 0.0000000000
##       3 0.0165509877 0.0005339028
##       4 0.0491467577 0.0013651877
```

```r
#Baseline percentages
QualityCounts = summary(factor(Wine$quality))
QualityCountsProp = QualityCounts/sum(QualityCounts)
QualityCountsProp
```

```
##           3           4           5           6           7           8
## 0.004617516 0.033246114 0.329074958 0.436509158 0.166076651 0.029706018
##           9
## 0.000769586
```

Not very well. None of the percentages in the cluster stand out as vastly different from the corresponding percentage in the baseline. Put another way, if you tell me a wine is in Cluster 3, I will not be able to tell you with any more certainty what quality wine it is versus just telling you what I could glean from the unclustered data (i.e., a quality of 6 is most)

Performance is somewhat good. For example, in the baseline, 43% of wines are quality 6 while 33% are quality 5. But in cluster 4, the difference is more pronounced - 47% of cluster 4 wines are quality 6 while 21% are cluster 5. Conversely, in cluster 2, 50% of wines are quality 5 while 36% are cluster 6. So I can do a little better than just guessing the most common quality if the wine is in cluster 2.

Principal Component Analysis (PCA)

Overall, I was pretty happy with the performance of my clusters. Will I be able to top it using PCA?

```r
WinePrincipalComponent = prcomp(WineScaled)
loadings = WinePrincipalComponent$rotation
scores = WinePrincipalComponent$x
loadings[,1:2]
```

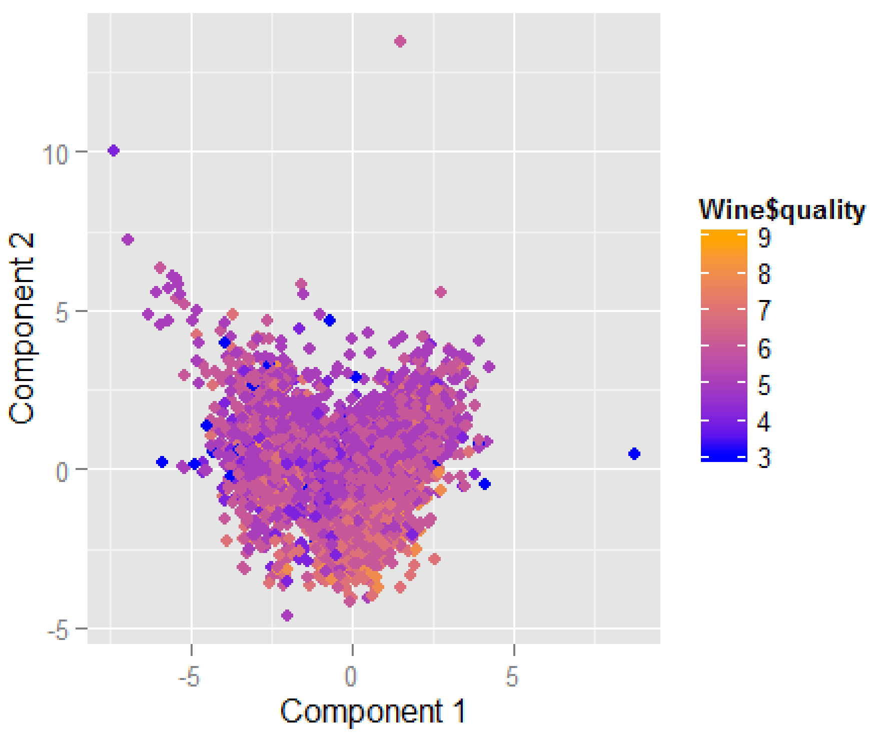
```
##                              PC1         PC2
## fixed.acidity        -0.23879890  0.33635454
## volatile.acidity     -0.38075750  0.11754972
## citric.acid           0.15238844  0.18329940
## residual.sugar        0.34591993  0.32991418
## chlorides            -0.29011259  0.31525799
## free.sulfur.dioxide   0.43091401  0.07193260
## total.sulfur.dioxide  0.48741806  0.08726628
## density              -0.04493664  0.58403734
## pH                   -0.21868644 -0.15586900
## sulphates            -0.29413517  0.19171577
## alcohol              -0.10643712 -0.46505769
```

```r
head(scores[,1:2])
```

```
##            PC1       PC2
## [1,] -3.205749 0.4164913
## [2,] -3.038817 1.1073769
## [3,] -3.071657 0.8788968
## [4,] -1.571141 2.1123820
## [5,] -3.205749 0.4164913
## [6,] -3.011934 0.3893675
```

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


```
qplot(scores[,1], scores[,2], color=Wine$quality, xlab='Component 1',
ylab='Component 2') + scale_color_gradient(low="blue", high="orange")
```



Looking at the first two components, I cannot determine quality with any accuracy. However, the reds and whites are very nicely split, and that's looking almost solely across component 1. I am unaware of how to quantify a classification rate based on PCA, but just looking at the picture, I prefer PCA to Clustering for distingushing red wines from white wines.

Market Segmentation

Using Social Media Data to Find Similar Customers

As always, the first step is to read in the data.

```
SocialMediaURLString =
getURL("https://raw.githubusercontent.com/jacebarton/STA380/master/data/socia
l_marketing.csv", ssl.verifypeer=0L, followlocation = 1L)
SocialMedia = read.csv(text=SocialMediaURLString)
summary(SocialMedia)
```

```
##          X            chatter       current_events      travel
##  123pxkyqj:   1   Min.   : 0.000   Min.   :0.000   Min.   : 0.000
##  12grikctu:   1   1st Qu.: 2.000   1st Qu.:1.000   1st Qu.: 0.000
##  12klxic7j:   1   Median : 3.000   Median :1.000   Median : 1.000
##  12t4msroj:   1   Mean   : 4.399   Mean   :1.526   Mean   : 1.585
##  12yam59l3:   1   3rd Qu.: 6.000   3rd Qu.:2.000   3rd Qu.: 2.000
##  132y8f6aj:   1   Max.   :26.000   Max.   :8.000   Max.   :26.000
##  (Other)  :7876
##  photo_sharing    uncategorized     tv_film      sports_fandom
##  Min.   : 0.000   Min.   :0.000   Min.   : 0.00   Min.   : 0.000
##  1st Qu.: 1.000   1st Qu.:0.000   1st Qu.: 0.00   1st Qu.: 0.000
##  Median : 2.000   Median :1.000   Median : 1.00   Median : 1.000
##  Mean   : 2.697   Mean   :0.813   Mean   : 1.07   Mean   : 1.594
##  3rd Qu.: 4.000   3rd Qu.:1.000   3rd Qu.: 1.00   3rd Qu.: 2.000
##  Max.   :21.000   Max.   :9.000   Max.   :17.00   Max.   :20.000
##
##     politics           food            family        home_and_garden
##  Min.   : 0.000   Min.   : 0.000   Min.   : 0.0000   Min.   :0.0000
##  1st Qu.: 0.000   1st Qu.: 0.000   1st Qu.: 0.0000   1st Qu.:0.0000
##  Median : 1.000   Median : 1.000   Median : 1.0000   Median :0.0000
##  Mean   : 1.789   Mean   : 1.397   Mean   : 0.8639   Mean   :0.5207
##  3rd Qu.: 2.000   3rd Qu.: 2.000   3rd Qu.: 1.0000   3rd Qu.:1.0000
##  Max.   :37.000   Max.   :16.000   Max.   :10.0000   Max.   :5.0000
##
##      music             news         online_gaming       shopping
##  Min.   : 0.0000   Min.   : 0.000   Min.   : 0.000   Min.   : 0.000
##  1st Qu.: 0.0000   1st Qu.: 0.000   1st Qu.: 0.000   1st Qu.: 0.000
##  Median : 0.0000   Median : 0.000   Median : 0.000   Median : 1.000
##  Mean   : 0.6793   Mean   : 1.206   Mean   : 1.209   Mean   : 1.389
##  3rd Qu.: 1.0000   3rd Qu.: 1.000   3rd Qu.: 1.000   3rd Qu.: 2.000
```

```
##  Max.   :13.0000   Max.   :20.000   Max.   :27.000   Max.   :12.000  
##                                                                       
##  health_nutrition  college_uni     sports_playing      cooking      
##  Min.   : 0.000   Min.   : 0.000   Min.   :0.0000   Min.   : 0.000  
##  1st Qu.: 0.000   1st Qu.: 0.000   1st Qu.:0.0000   1st Qu.: 0.000  
##  Median : 1.000   Median : 1.000   Median :0.0000   Median : 1.000  
##  Mean   : 2.567   Mean   : 1.549   Mean   :0.6392   Mean   : 1.998  
##  3rd Qu.: 3.000   3rd Qu.: 2.000   3rd Qu.:1.0000   3rd Qu.: 2.000  
##  Max.   :41.000   Max.   :30.000   Max.   :8.0000   Max.   :33.000  
##                                                                       
##       eco           computers          business         outdoors      
##  Min.   :0.0000   Min.   : 0.0000   Min.   :0.0000   Min.   : 0.0000  
##  1st Qu.:0.0000   1st Qu.: 0.0000   1st Qu.:0.0000   1st Qu.: 0.0000  
##  Median :0.0000   Median : 0.0000   Median :0.0000   Median : 0.0000  
##  Mean   :0.5123   Mean   : 0.6491   Mean   :0.4232   Mean   : 0.7827  
##  3rd Qu.:1.0000   3rd Qu.: 1.0000   3rd Qu.:1.0000   3rd Qu.: 1.0000  
##  Max.   :6.0000   Max.   :16.0000   Max.   :6.0000   Max.   :12.0000  
##                                                                         
##      crafts         automotive           art             religion     
##  Min.   :0.0000   Min.   : 0.0000   Min.   : 0.0000   Min.   : 0.000  
##  1st Qu.:0.0000   1st Qu.: 0.0000   1st Qu.: 0.0000   1st Qu.: 0.000  
##  Median :0.0000   Median : 0.0000   Median : 0.0000   Median : 0.000  
##  Mean   :0.5159   Mean   : 0.8299   Mean   : 0.7248   Mean   : 1.095  
##  3rd Qu.:1.0000   3rd Qu.: 1.0000   3rd Qu.: 1.0000   3rd Qu.: 1.000  
##  Max.   :7.0000   Max.   :13.0000   Max.   :18.0000   Max.   :20.000  
##                                                                          
##      beauty          parenting           dating            school       
##  Min.   : 0.0000   Min.   : 0.0000   Min.   : 0.0000   Min.   : 0.0000  
##  1st Qu.: 0.0000   1st Qu.: 0.0000   1st Qu.: 0.0000   1st Qu.: 0.0000  
##  Median : 0.0000   Median : 0.0000   Median : 0.0000   Median : 0.0000  
##  Mean   : 0.7052   Mean   : 0.9213   Mean   : 0.7109   Mean   : 0.7677  
##  3rd Qu.: 1.0000   3rd Qu.: 1.0000   3rd Qu.: 1.0000   3rd Qu.: 1.0000  
##  Max.   :14.0000   Max.   :14.0000   Max.   :24.0000   Max.   :11.0000  
##                                                                           
##  personal_fitness    fashion        small_business        spam        
##  Min.   : 0.000   Min.   : 0.0000   Min.   :0.0000   Min.   :0.00000  
##  1st Qu.: 0.000   1st Qu.: 0.0000   1st Qu.:0.0000   1st Qu.:0.00000  
##  Median : 0.000   Median : 0.0000   Median :0.0000   Median :0.00000  
##  Mean   : 1.462   Mean   : 0.9966   Mean   :0.3363   Mean   :0.00647  
##  3rd Qu.: 2.000   3rd Qu.: 1.0000   3rd Qu.:1.0000   3rd Qu.:0.00000  
##  Max.   :19.000   Max.   :18.0000   Max.   :6.0000   Max.   :2.00000  
##                                                                         
##      adult        
##  Min.   : 0.0000  
##  1st Qu.: 0.0000  
##  Median : 0.0000  
##  Mean   : 0.4033  
##  3rd Qu.: 0.0000  
##  Max.   :26.0000  
##
```

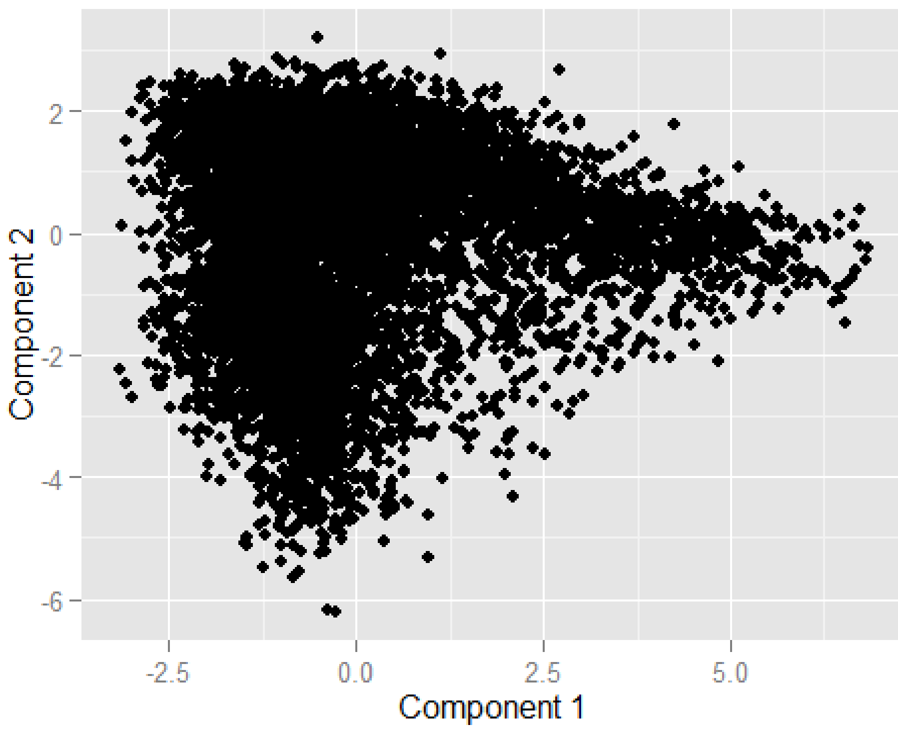
Now, I need to find the frequency of the content types for each user rather than the count.

```
# Normalize phrase counts to phrase frequencies
SocialMediaFrequencies = SocialMedia[,-1]/rowSums(SocialMedia[,-1])
```

And now, since I'm feeling wild, I'll perform PCA analysis *first* instead of cluster analysis. I know, try to contain your excitement.

PCA for Social Media Data

```
SocialMediaPCA = prcomp(SocialMediaFrequencies, scale=TRUE)
SMLoadings = SocialMediaPCA$rotation
SMScores = SocialMediaPCA$x

qplot(SMScores[,1], SMScores[,2], xlab='Component 1', ylab='Component 2')
```



Unlike the wine data, there's not an output variable for me to look at on a plot of Component 1 vs Component 2. Instead, I can try looking at the features which score highest on each component, starting with component 1.

```
Component1Ordered = order(SMLoadings[,1])
colnames(SocialMediaFrequencies)[tail(Component1Ordered,5)]

## [1] "school"        "food"          "parenting"     "sports_fandom"
## [5] "religion"
```

Religion scores highest, followed by sports_fandom and parenting (note that the highest score is the last entry).

```r
Component2Ordered = order(SMLoadings[,2])
colnames(SocialMediaFrequencies)[tail(Component2Ordered,5)]

## [1] "automotive" "shopping"   "travel"     "politics"   "chatter"
```

In Component 2, chatter, politics, and travel score highest.

Now, I'll see if some of these patterns hold when I look at the clustered data.

Social Media Clusters

Similar to the wine problem, I will use CH(k) to determine what number of clusters to use.

```r
PossibleKsSocial = matrix(0, nrow=19, ncol=2)
PossibleKsSocial[,1] = 2:20
set.seed(722)
for(i in 1:19){
  SocialKMeanClusters = kmeans(SocialMediaFrequencies, i, nstart=50)
  CHk = ((SocialKMeanClusters$betweenss/(i-
1))/(SocialKMeanClusters$tot.withinss/(nrow(SocialMediaFrequencies)-i)))
  PossibleKsSocial[i,2] = CHk
}

## Warning: did not converge in 10 iterations

## Warning: Quick-TRANSfer stage steps exceeded maximum (= 394100)

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

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## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

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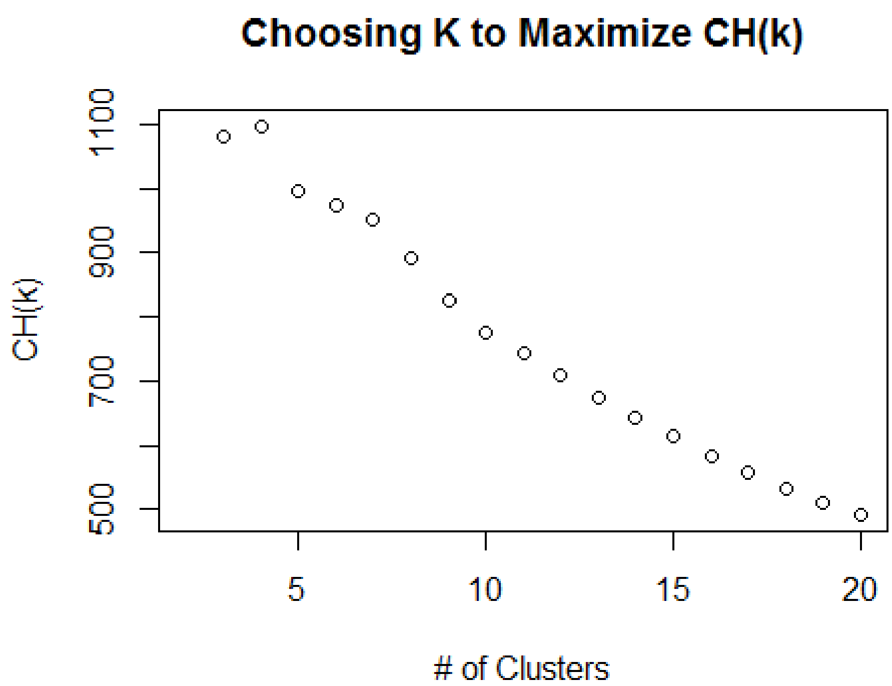

```
## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

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

```
plot(PossibleKsSocial, xlab="# of Clusters", ylab="CH(k)", main="Choosing K
to Maximize CH(k)")
```



Yet again, four clusters is the optimal choice. I will add the cluster values to the original social media data.

```
set.seed(722)
SocialKMeanClusters = kmeans(SocialMediaFrequencies, 4, nstart=50)
SocialMedia$cluster = factor(SocialKMeanClusters$cluster)

summary(factor(SocialKMeanClusters$cluster))

##    1    2    3    4
## 1417 3437  807 2221
```

Now, I'll look at the five most significant features for each cluster.

```
sort(SocialKMeanClusters$centers[1,], decreasing=TRUE)[1:5]

## health_nutrition personal_fitness          chatter          cooking
##       0.21192108       0.10608338       0.07639196       0.05458727
##         outdoors
##       0.04303909
```

```r
sort(SocialKMeanClusters$centers[2,], decreasing=TRUE)[1:5]
```

```
##       chatter      politics sports_fandom   college_uni        travel
##    0.07714131    0.06247846    0.05596013    0.05293592    0.05251692
```

```r
sort(SocialKMeanClusters$centers[3,], decreasing=TRUE)[1:5]
```

```
##       cooking photo_sharing       fashion       chatter        beauty
##    0.18541240    0.09484052    0.09099594    0.07366347    0.05922135
```

```r
sort(SocialKMeanClusters$centers[4,], decreasing=TRUE)[1:5]
```

```
##        chatter  photo_sharing       shopping current_events         travel
##     0.23012456     0.11417367     0.06582203     0.05626872     0.03543507
```

The only feature from the first component to appear in the clusters' most significant features is sports_fandom. From the second component, chatter appears in all 4 clusters, while politics appears in 1, travel appears in 2, shopping appears in 1, and automotive appears in 0.

Given the difficulty in interpreting PCA in this case, I will base my analysis off of the clusters. The clusters also make sense. For example, health-nutrition, personal fitness, and outdoors all appear in a cluster together, while sports-fandom and college-uni also appear in a cluster together. Additionally, fashion and beauty appear in a cluster. These are three good market segments to begin to target amongst the company's customers.