

# Modeling 2 Final

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## Question 1 - Green Buildings

1

From the beginning, I'm suspicious of the excel guru's analysis because first, he cut out buildings that had less than 10% occupancy. This did not take into account the age of the building. If it was developed in the last six months or a year, this less than 10% rule should not be applicable to the building. Yes, there are cases where this less than 10% metric could be a telling factor of the quality of the building or administration, it should not be used as a blanket statement that  $\leq 10\%$  occupancy is bad. Secondly, he just took an average of the rent of non-green buildings and green buildings to then forecast premium rent rates of green buildings. He completely disregarded the 21 other variables that could have been used.

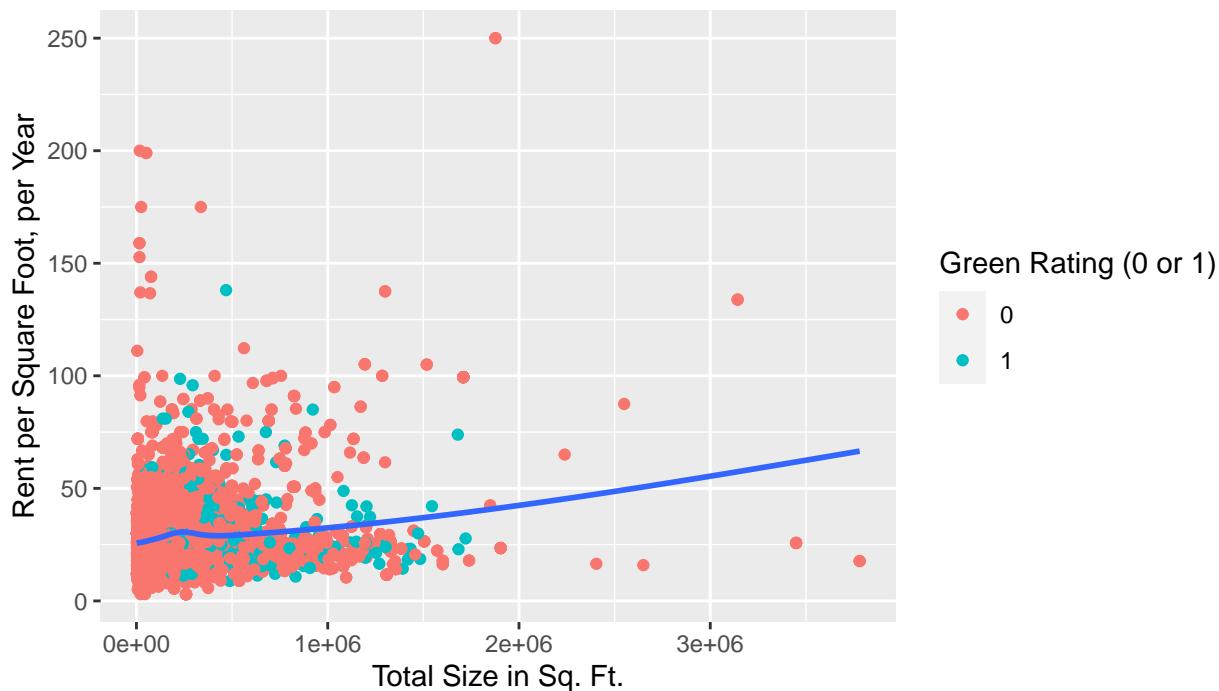
```
## 'geom_smooth()' using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

### Rent as a function of Size

Mean size = 234,637.74 sqft.

Green Buildings Mean Size = 325,781.32 sqft.

Non-Green Buildings Mean Size = 225,977.27 sqft.



This initial plot shows how Rent changes as the total size of the building increases. While the fitted line is not a good predictor, we can see that the rent price does increase as size of the building increases.

Green buildings have a higher mean building size than standard ones, which can be a reason to believe that green buildings are able to fetch higher rent prices.

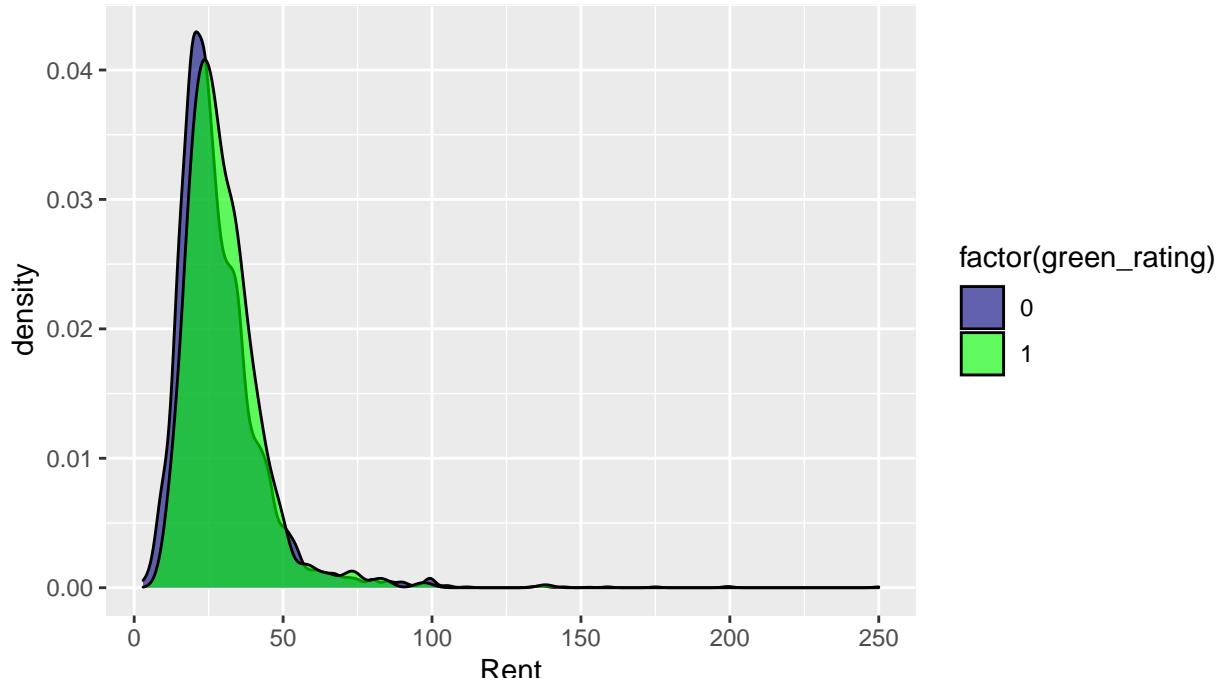
2

### Standard vs Green Density

Median Rent = \$25.16/sqft./yr.

Green Buildings' Median Rent = \$27.6/sqft./yr.

Standard Buildings' Median Rent = \$25/sqft./yr.



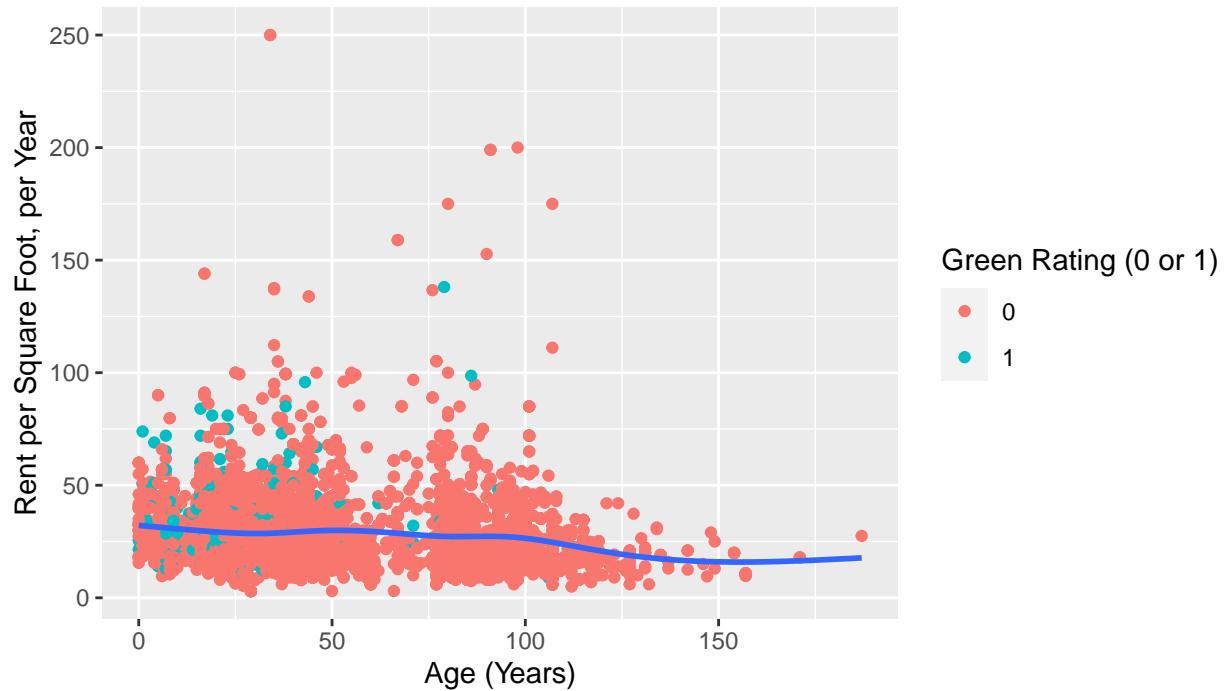
Here we can see that while green buildings have a slightly higher median compared to standard buildings, they are practically identical. This slightly higher median rent could be attributed to the on average larger building size of the green buildings, but we must look into more variables to get a better idea.

3

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

## Rent as a function of Age

Average Age = 47.24 years  
Average Green Age = 23.85 years  
Average Standard Age = 49.47 years



With age, we can see that there is a gradual decrease in rent as the building ages, but there are many outliers that charge very high rent rates.

Since there is a negative correlation between age and rent prices, and green buildings have a much lower average age compared to the overall average, we inferred that this can leads to generally higher rent prices for green buildings.

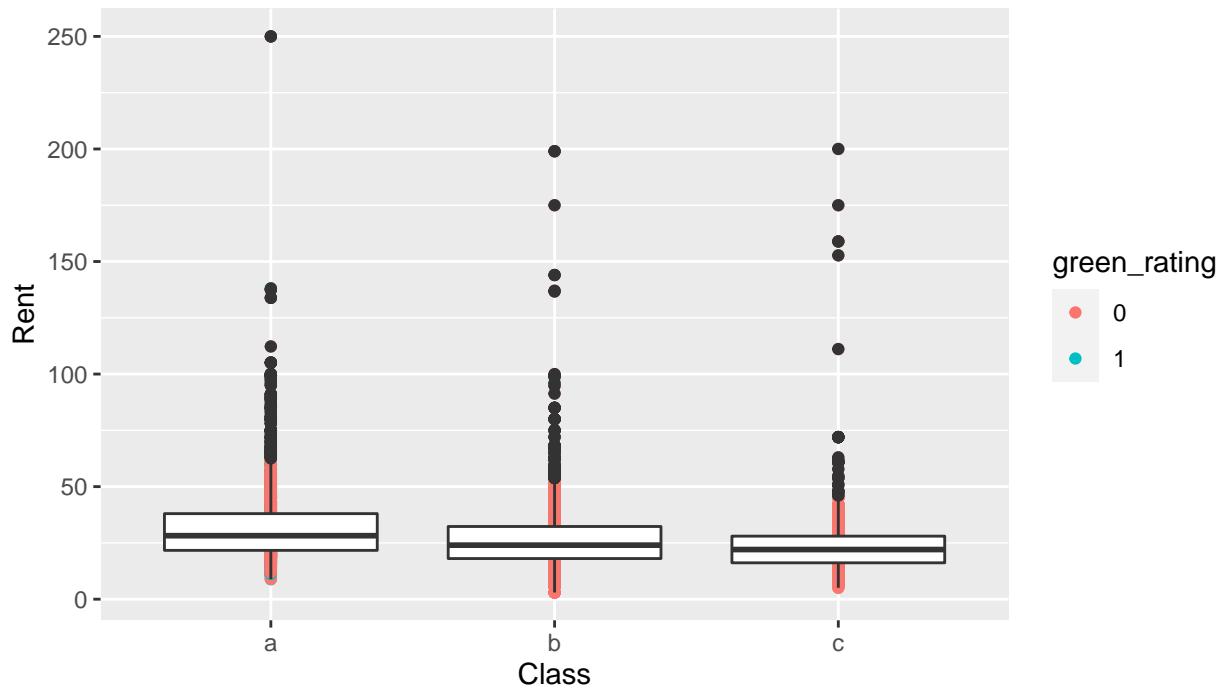
This factor coupled with their higher than average sizes supports the assumption that buildings with green status can charge a premium in rent.

### Box plot for each class type

Avg. Price Class "A" = \$32.32

Avg. Price Class "B" = \$26.39

Avg. Price Class "C" = \$23.94



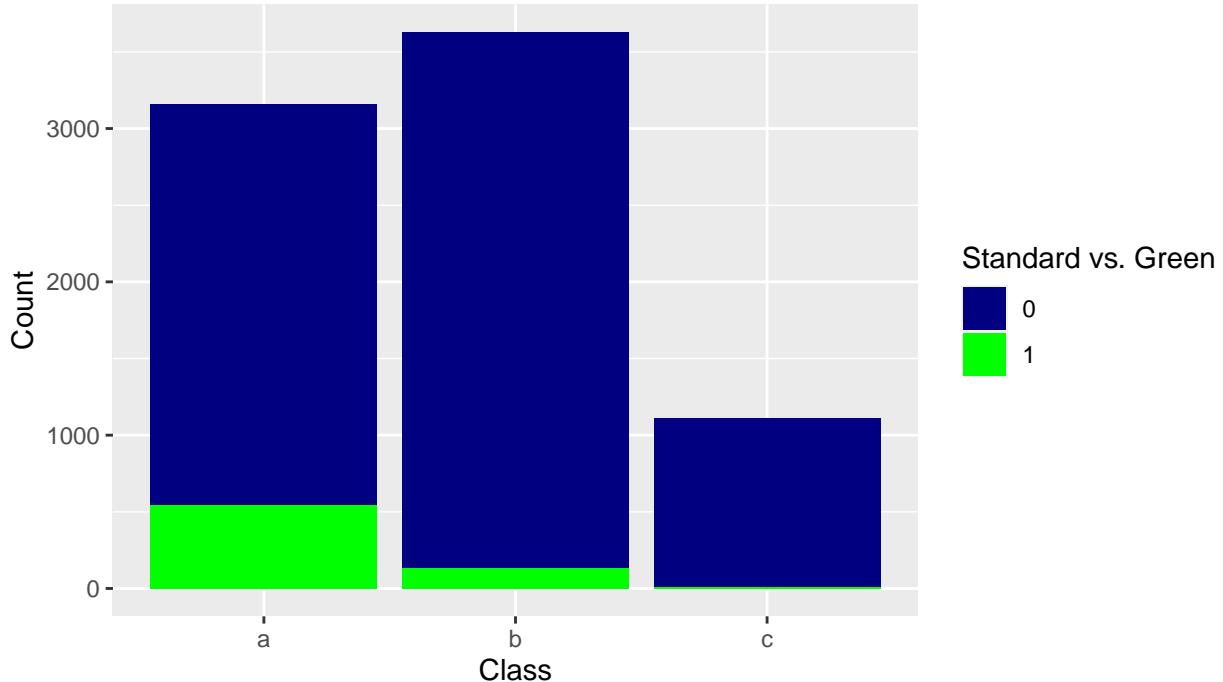
After seeing how Rent changes as a function of numeric variables age and size, we wanted to see how class affects rent. Of course, the highest class building, class A, has the highest median and range, followed by B then C.

## Proportion of Green vs. Standard

Proportion of green buildings that are class A = 79.71% (546)

Proportion of green buildings that are class B = 19.27% (132)

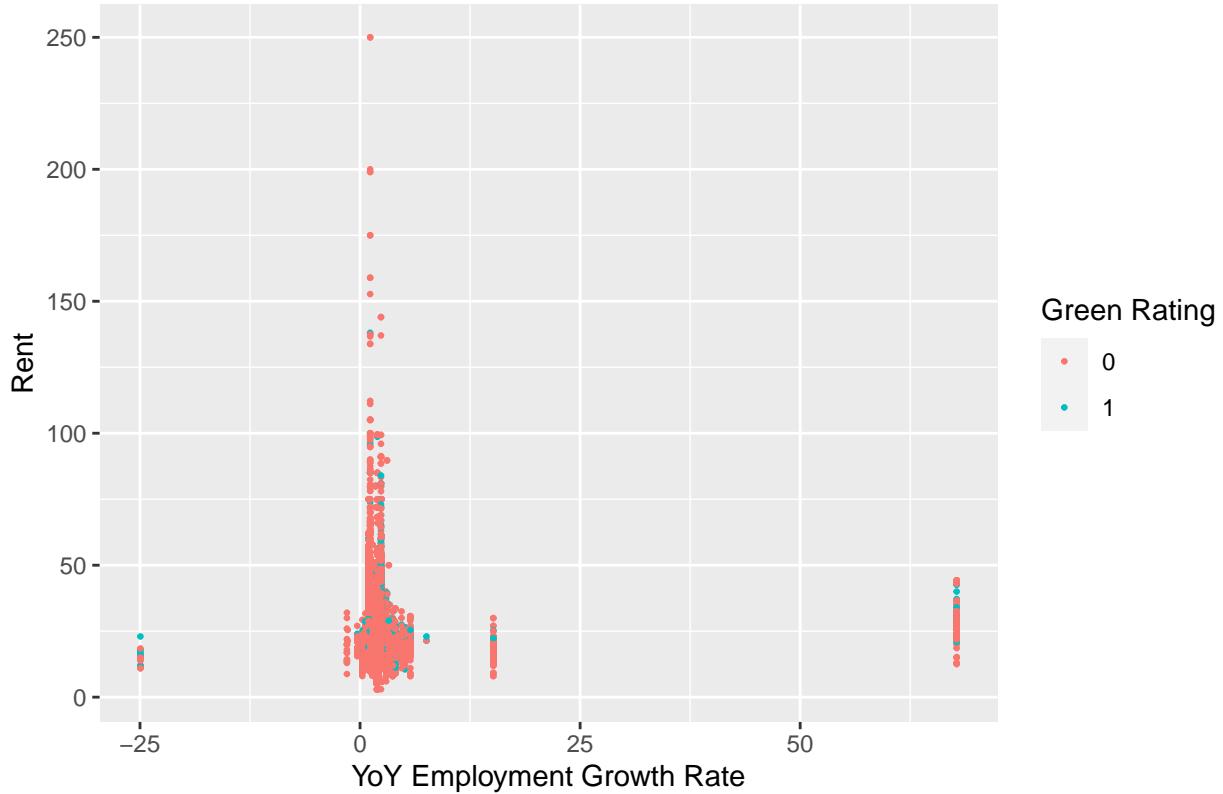
Proportion of green buildings that are class C = 1.02% (7)



Here we can see that out of the three classes, green has it's highest number in class A. As we saw above, class A is also the most expensive classification of building. Based on green buildings being nearly 80% class A, one can claim that there is a positive correlation between green status and higher rent prices; if someone were to randomly pick a green building, 4/5 times they would choose a class A, the highest price class.

```
## Warning: Removed 74 rows containing missing values (geom_point).
```

## Rent as a function of YoY Employment Growth Rate by Region



We were curious on how Rent prices fluctuated, given the year-over-year employment growth rate that each building's region was seeing. While there is a very slight increase in the range of rent prices from the subsets 15% to 60%, we decided that this data is inconclusive. The majority grouping of buildings in the 0-7.5% range has such a wide range of rent prices that it appears that growth rate does not affect rent prices charged.

### Conclusion

From the three variables tested that provided substantial evidence (Size, Age, and Class), they indirectly showed that people paid a premium for green buildings. While this does support the stats guru's conclusion that the company could price the rent of a green building at a premium, we do not believe that these conclusions provide enough evidence to concretely say that any green building can charge a premium. What we did conclude is that the company should focus more on is the overall size of the building and developing one that would be of class A.

Size - Since buildings that are larger generally charge higher prices on average, the company should research developing a building larger than average (234,638 sqft.). Class - Buildings that are of class A, on average charge the highest rent prices at \$32.32/sqft., while class B and class C charge \$26.39/sqft. and \$23.94/sqft., respectively.

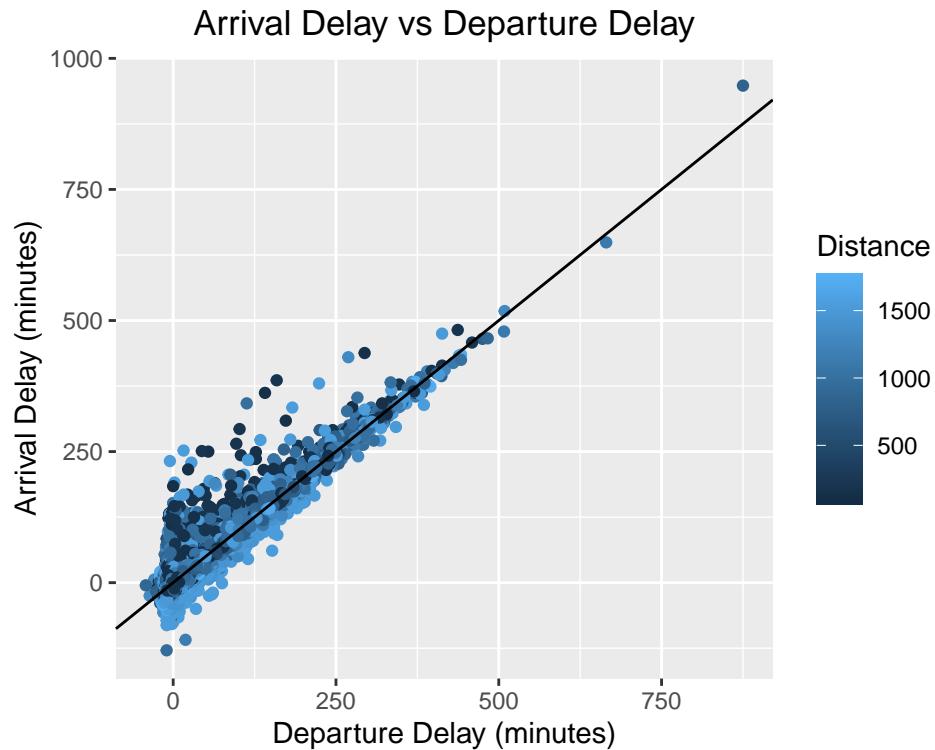
While we cannot say with certainty that a building that has received a green rating equates to being able to charge a premium over non-green rated buildings, we do believe that a further in-depth analysis on other variables should be taken generate this answer.

## Question 2 - ABIA

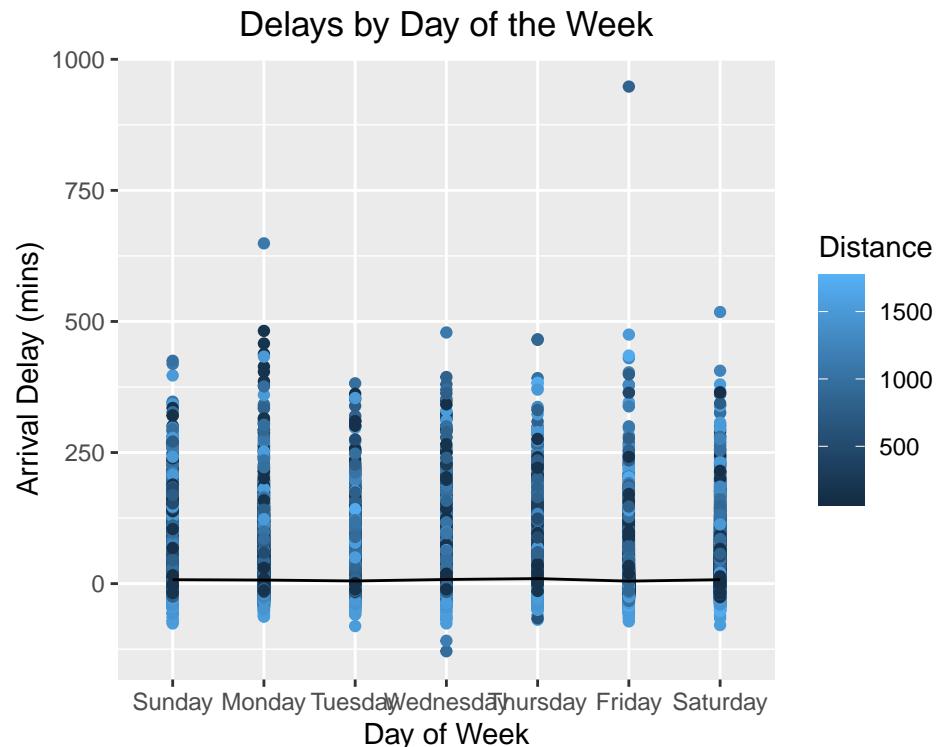
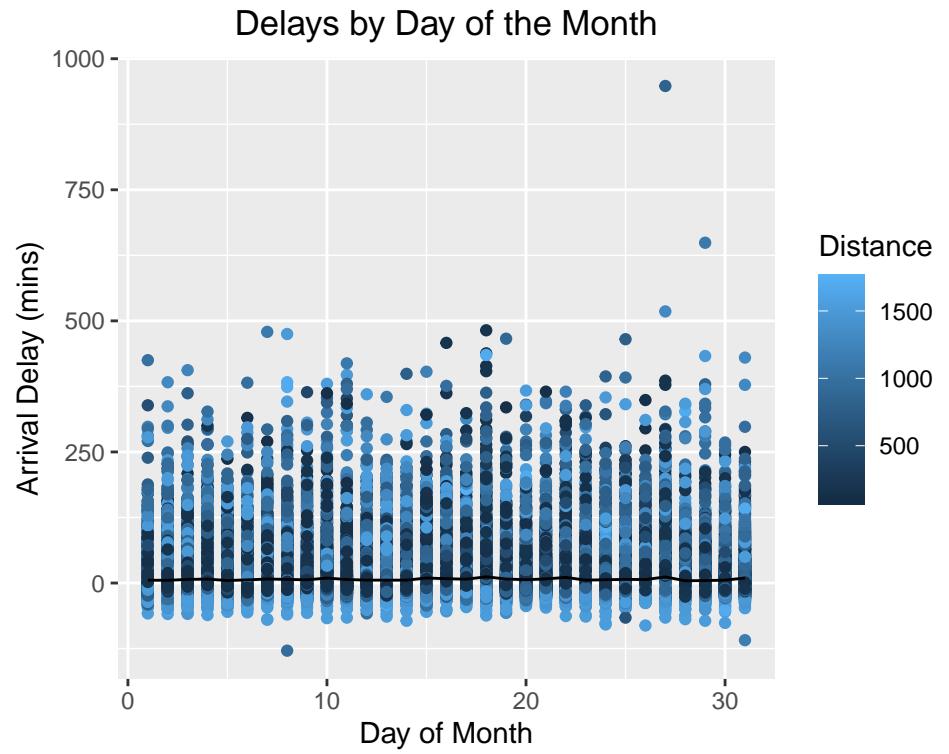
### Flights at ABIA

*Visual Story Telling:* Create a set of related figures that tell an interesting story about flights into and out of Austin.

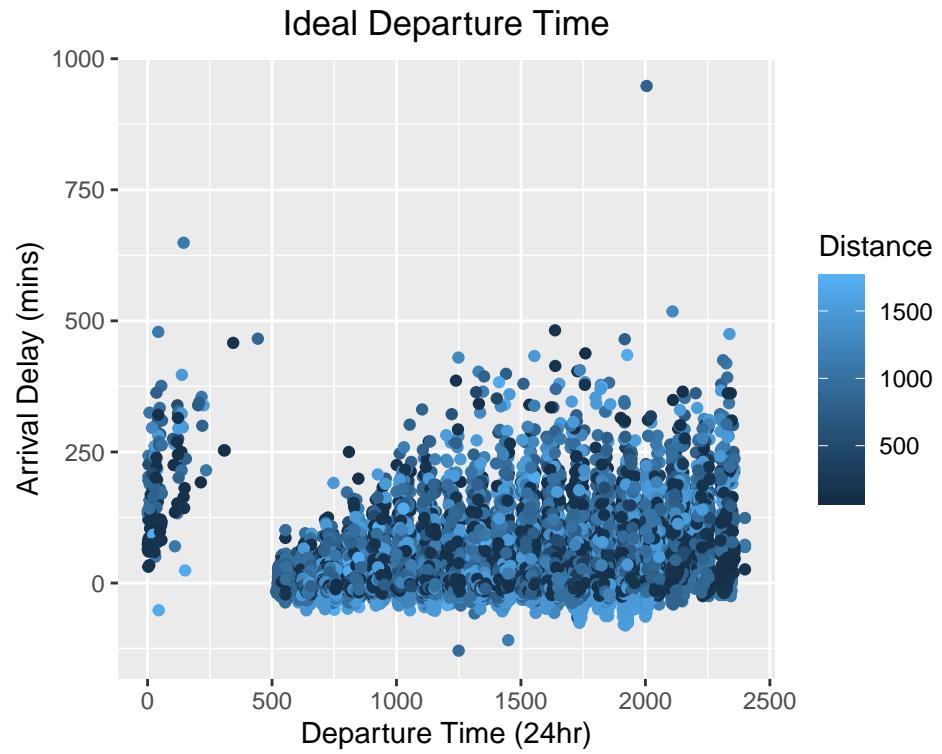
Given information about Arrival and Departure Delays, what insights can we gather?



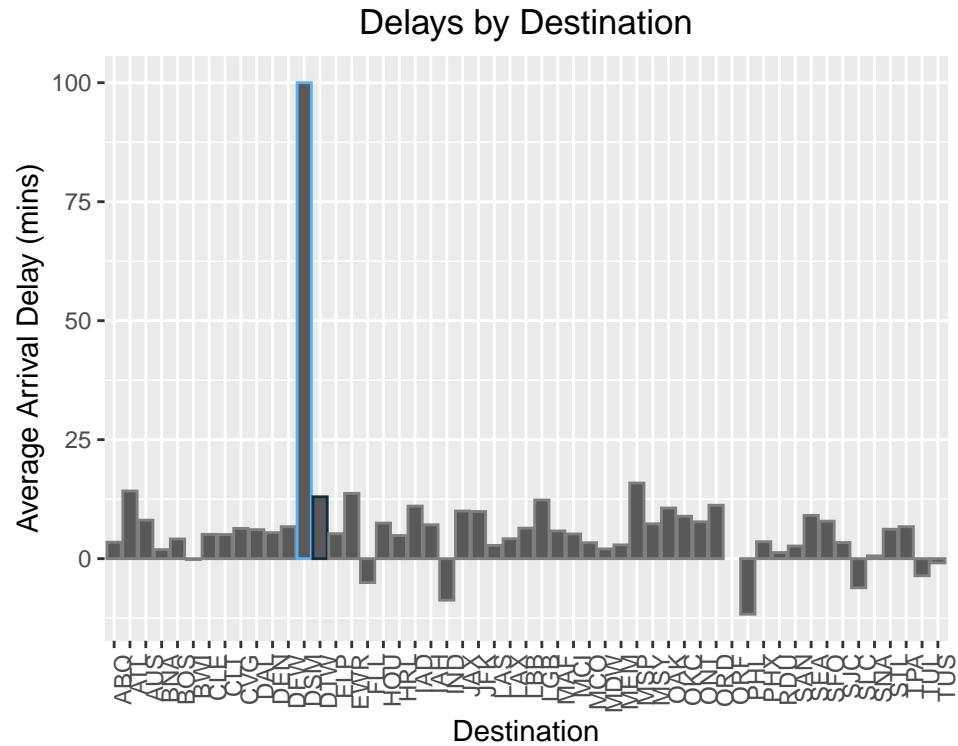
First, we plot the relationship between departure and arrival delays. This result shows, not surprisingly, that there is a relationship of approximately  $y=x$ . Arrival delays have a tendency to be higher, suggesting in-air delays, such as circling for an available runway on approach. Because arrival delays tend to have a greater influence on flying experience (particularly for connecting flights), we will use arrival delays in our analysis.



Are there any days you should avoid flying? Arrival delay is plotted against day of the month and day of the week. While there are some slight deviations, the average delay is negligible in either plot (with an overall average of 7.06 mins). Just three days of the month have an average delay over 10 minutes: the 18th, 22nd and 27th. Thursday has the highest average delay at 9.55 minutes.

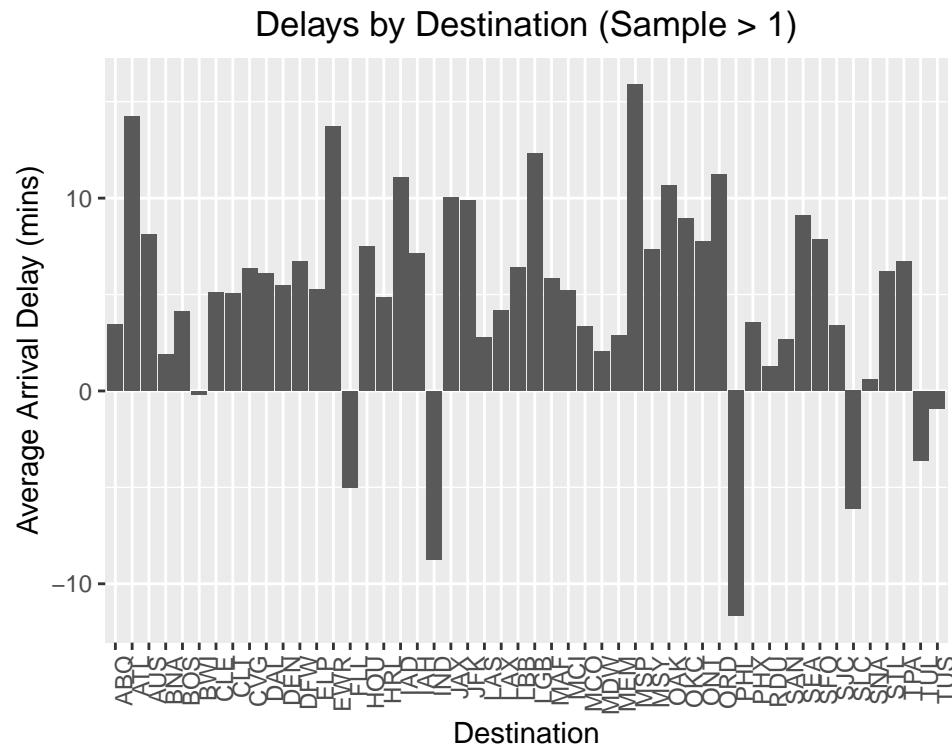


Next, we look at the best time of day to fly. Intuitively, as the day goes on, delays appear to grow. This follows a common idea that delayed flights in the morning have a domino effect on flights throughout the day. The best time to schedule a flight to avoid a delay is between 5am and 8am.

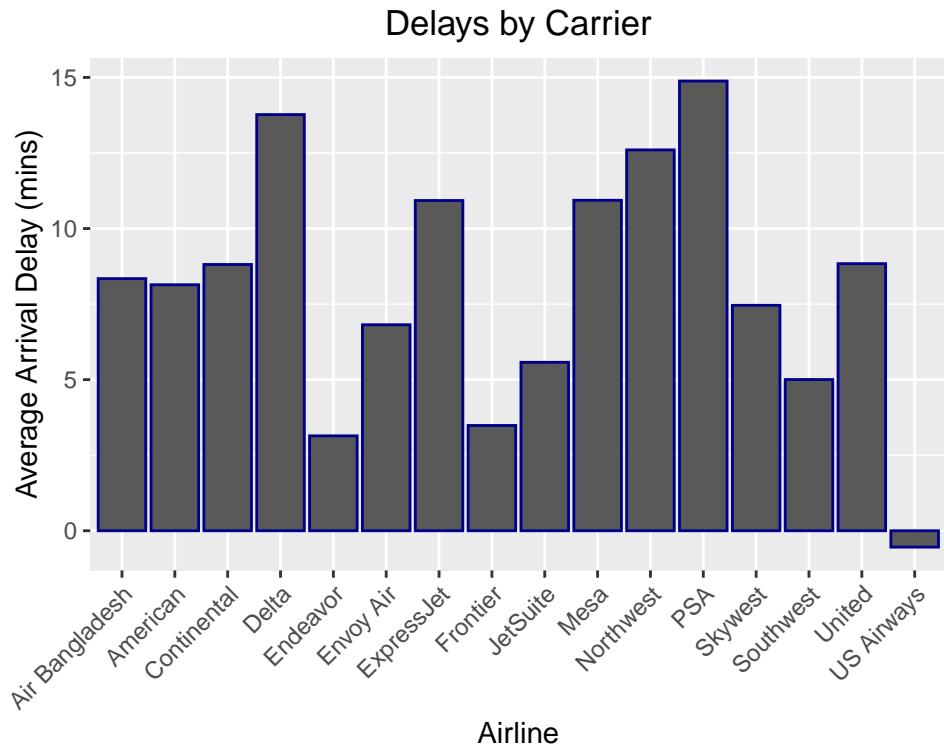


Are there any airports to avoid? Based on average arrival delay, it seems that we should never fly to Des

Moines (DSM) as it has the highest average delay by a wide margin. However, upon further inspection, there is only data from a single flight from DSM in the set.



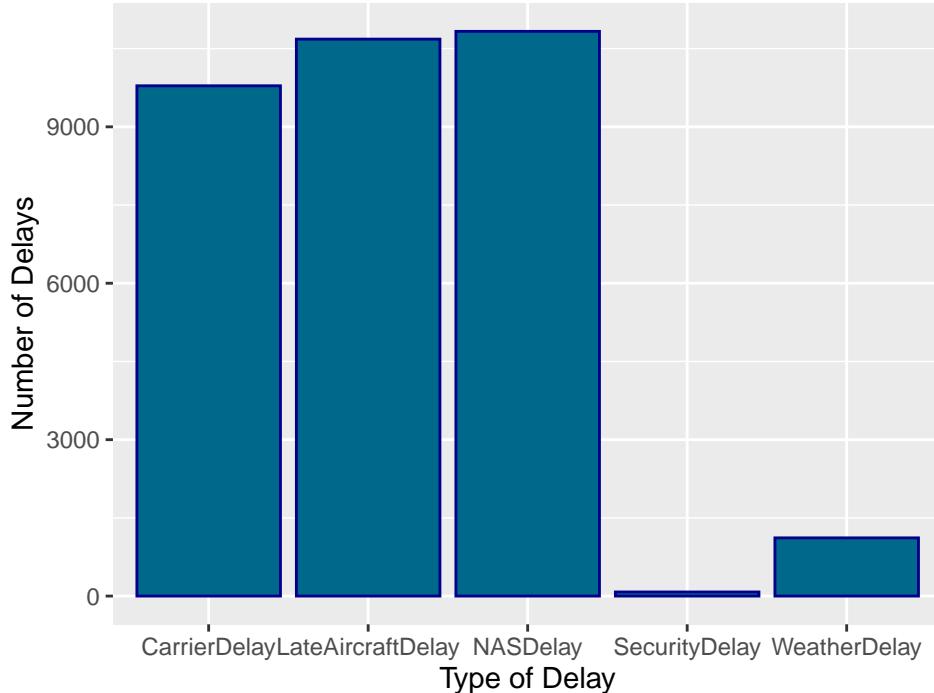
Excluding destinations with one flight (DSM, DTW and ORF), New Orleans (MSP) is now the airport with the longest average delay of over 15 minutes. In contrast, flights going into Baltimore (BWI), Fort Lauderdale (FLL), Indianapolis (IND), Philadelphia (PHL), Salt Lake City (SLC), Tulsa (TUL), and Tucson (TUS) all actually arrive ahead of schedule, on average. These are the best airports to fly into if leaving Austin and



looking to avoid a delay.

Which carriers are most likely to be delayed? Based on average arrival delay, PSA Airlines is the most likely to be responsible for your missed connection, followed by Delta. On the other end of the spectrum, US Airways is the only carrier that will, on average, get you there ahead of schedule.

### Number of Delays Recorded by Type



Finally, what's causing all these delays anyway? Clearly, Carrier Delays, Late Aircraft, and NAS (National

Aviation System) Delays are the most significant culprits, with Security and Weather Delays relatively infrequent. This can be misleading, however, as NAS delays include all *non-extreme* weather issues, which can be reduced with corrective action by airports or the FAA, among other factors like heavy air traffic and airport operations issues. Weather Delays only refer to rare extreme weather events that cannot be mitigated.

## Question 3 - Portfolio Modeling

### Selecting the ETFS:

In constructing our portfolio of ETF's we wanted to select a subgroup that could itself be arranged into separate portfolios of differing characteristics, but still be sufficiently diversified. Our first selection was EMB, J.P. Morgan's emerging markets bond ETF, chosen due to recent data showing emerging market bond's outperforming US and European bond ETFs. We then chose IEF, an ETF tracking 7-10 year treasury bonds, generally seen as a relatively safe, albeit underperforming, fixed income group. DVY, the iShares Select Dividend ETF, was chosen to provide our portfolio some consistent income. VIXY, a short-term volatility index, was chosen to take advantage of the current levels of volatility. XLF, the Financial Sector Select SPDR fund, was chosen to take advantage of the returns that financial services tend to provide, but have provided in a surprising way during the COVID recession. XLV is a Health Care index and was chosen as somewhat of a bet that health care related firms would be receiving some level of stimulus and a lot of attention, both from customers and investors, as treatments for COVID and distribution of PPE is widely sought after. Chosing VGK, the Vanguard FTSE Europe ETF, was due in large part to the recent stimulus package approved by EU nations that should bolster the gradual reopening we are seeing in Europe that should lead to some positive returns over the coming quarters for EU based firms. Furthermore, gaining exposure to Europe, the only major market so far neglected in the portfolio provides some naive diversification at the very least. XLP is a consumer staples ETF that should see some positive returns, and has had some very positive returns over the last 6 months, as customers are rushing to stock up on staple goods. QLD is a leveraged equity ETF that tracks the Nasdaq-100 index and seeks to return 2x the returns of the its underlying index. Given the recent returns of tech companies, which make up a considerable portion of the Nasdaq, which should continue as the US remains relatively locked down, this seemed like a very safe investment. Finally, the IWN, which tracks the Russell 2000, was chosen as a means of gaining exposure to small-cap value stocks, securities that have seen generally positive returns over growth stocks, and idea that serves as the basis for the Fama-French valuation model.

### Selecting the First Portfolio

While a three security portfolio is generally never a great idea, due to lack of diversification, we decided to construct one anyways to at least prove in subsequent iterations why more securities in a portfolio will generally provide better, or less volatile, returns.

The portfolio selected included our IEF, DVY, and VGK ETFs, which represent our safest selections. Fixed income and dividends, mixed with a European equity ETF, should provide relatively stable returns without introducing much risk. The first step was binding the returns, setting equal weights, then running the bootstrap to simulate returns over a 4 week period.

```
#Bind first row into return matrix
small_returns = cbind(C1C1(IEFa), C1C1(DVYa), C1C1(VGKa))

small_returns = as.matrix(na.omit(small_returns))
N = nrow(small_returns)

initial_wealth = 100000
my_weights1 = c(1/3,1/3,1/3)
```

```

set.seed(1234)

small_sim = foreach(i=1:5000, .combine='rbind') %do% {
  total_wealth = initial_wealth
  weights = my_weights1
  holdings = weights*total_wealth
  n_days = 20
  wealthtracker = rep(0,n_days)
  for(today in 1:n_days) {
    return.today = resample(small_returns,1,orig.ids=FALSE)
    holdings = weights*total_wealth
    holdings = holdings*(1+return.today)
    total_wealth = sum(holdings)
    holdings = weights*total_wealth
    wealthtracker[today] = total_wealth
  }
  wealthtracker
}

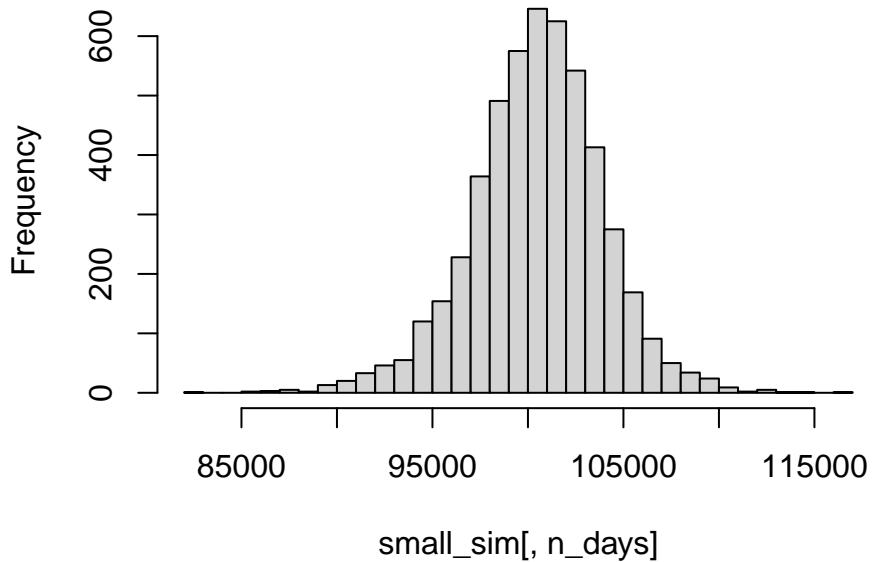
head(small_sim)

##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## result.1 100438.18 100490.12 100996.44 100427.89 101013.78 101103.59 101454.88
## result.2 100360.16 100128.85 101086.09 100542.25 100404.66 101207.00 101847.25
## result.3 100191.64 100991.57 101159.88 101134.93 98031.93 98890.49 98901.91
## result.4 99931.11 99195.55 98483.17 98576.38 97274.35 97907.31 98391.71
## result.5 99622.79 99617.88 99831.05 99821.26 99552.43 99885.02 99916.33
## result.6 99995.07 100588.57 100878.57 100179.44 100044.65 100194.19 100276.95
##          [,8]      [,9]      [,10]     [,11]     [,12]     [,13]     [,14]
## result.1 101572.10 101598.19 101932.91 101047.46 100800.59 100989.12 101263.44
## result.2 102063.81 101660.37 102683.81 102547.35 102219.66 102215.98 102115.85
## result.3 99226.16 99315.28 99208.18 99074.70 100147.48 100543.86 93227.99
## result.4 98063.86 98274.92 98458.72 98588.95 98570.32 98208.56 98088.66
## result.5 100158.64 99859.18 100054.72 99793.72 99546.13 99354.10 99650.15
## result.6 100392.82 100741.67 101043.08 100505.67 100518.24 100689.74 99185.86
##          [,15]     [,16]     [,17]     [,18]     [,19]     [,20]
## result.1 101271.19 101955.61 101177.86 101522.17 101742.03 101550.51
## result.2 102328.49 103034.49 104870.20 104816.33 104285.33 104011.75
## result.3 93699.71 93432.98 93841.14 93733.26 92809.40 93270.83
## result.4 98332.50 98473.20 97790.74 97278.41 96920.74 96916.27
## result.5 98445.24 97815.75 97668.36 97757.64 97655.48 97421.82
## result.6 98017.46 98806.53 99159.30 99093.34 100622.99 100668.34

hist(small_sim[,n_days], 25)

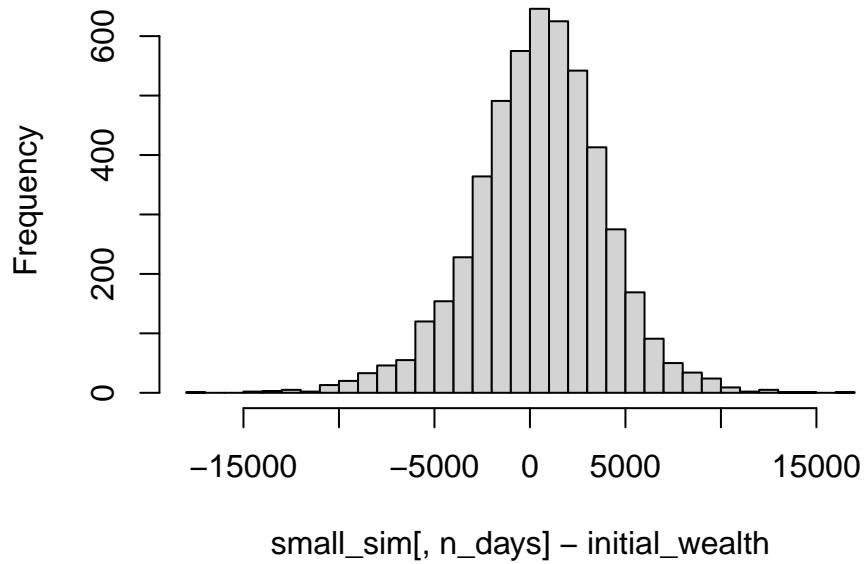
```

## Histogram of small\_sim[, n\_days]



```
mean(small_sim[,n_days])  
## [1] 100475.4  
mean(small_sim[,n_days] - initial_wealth)  
## [1] 475.3521  
hist(small_sim[,n_days] - initial_wealth, breaks=30)
```

## Histogram of small\_sim[, n\_days] – initial\_wealth



```
# 5% value at risk:  
quantile(small_sim[,n_days] - initial_wealth, prob=0.05)  
  
##           5%  
## -5341.957
```

Despite our best efforts to reduce volatility, it is clear in our results that we were not successful. Our mean return over the 20 day period was \$422.21. Not surprising given the fact that investments in fixed income and dividend stocks are generally not made for huge returns on equity, but rather for the provision of income and their relative safety in times of uncertainty.

It should be noted, however, that we are in a period of unprecedented uncertainty and a time in which treasury securities' returns are historically low. Given these two facts, it is equally unsurprising that our VaR, or Value at Risk, a measure that estimates how much a set of investments might lose at the 5% confidence interval, is -\$5,277.57. That is considerably more than our mean returns which shows that this is likely not a great portfolio to invest in at this time. Even though this is the least likely scenario, it is a measure that some investors put a lot of weight in given the relative increase in "black swan" events.

It should be noted of course that our distribution is centered around slightly positive returns, which means on average an investor can expect positive returns from this portfolio.

## Choosing the Second Portfolio

In choosing the second portfolio, we sought to build on the first rather than select a whole new subset of securities. We did this to stay consistent with our effort to show the effect of diversification in a portfolio. For this portfolio, we added three more securities, EMB, XLF, and QLD. We saw these additions as relatively aggressive additions because of the outsized returns that we expect these securities to provide in the current market conditions.

```
medium_returns = cbind(C1C1(IEFa), C1C1(DVYa), C1C1(VGKa), C1C1(EMBa),
                      C1C1(XLFa), C1C1(QLDa))

medium_returns = as.matrix(na.omit(medium_returns))
N = nrow(medium_returns)

initial_wealth = 100000
my_weights2 = c(1/6,1/6,1/6)

set.seed(1234)

medium_sim = foreach(i=1:5000, .combine='rbind') %do% {
  total_wealth = initial_wealth
  weights = my_weights2
  holdings = weights*total_wealth
  n_days = 20
  wealthtracker = rep(0,n_days)
  for(today in 1:n_days) {
    return.today = resample(medium_returns,1,orig.ids=FALSE)
    holdings = weights*total_wealth
    holdings = holdings*(1+return.today)
    total_wealth = sum(holdings)
    holdings = weights*total_wealth
    wealthtracker[today] = total_wealth
  }
  wealthtracker
}

head(medium_sim)

##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## result.1 100850.29 100978.28 102116.52 101305.41 102077.00 102519.03 102892.80
```

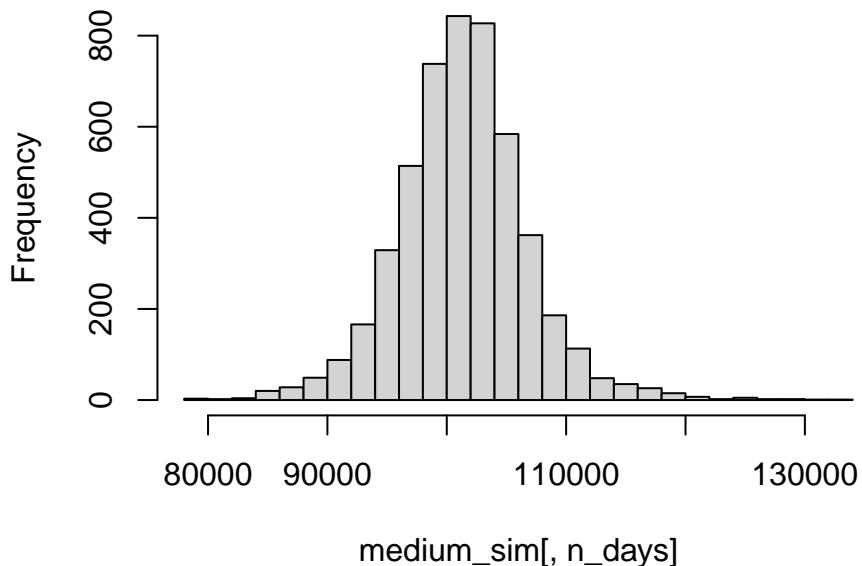
```

## result.2 100858.26 100484.63 101901.11 101154.42 101425.21 102841.46 104124.81
## result.3 100374.45 100842.59 100999.22 101271.86 96854.84 96699.92 96858.23
## result.4 100330.93 99327.96 98409.35 98256.40 96856.69 97674.74 98016.43
## result.5 99184.49 99201.46 99293.42 99383.69 99152.69 99615.76 99688.18
## result.6 100017.10 100883.99 101593.37 100525.27 100325.84 100216.68 100682.66
##      [,8]      [,9]      [,10]      [,11]      [,12]      [,13]      [,14]
## result.1 103018.23 103011.87 103916.09 102593.90 101738.74 102026.27 102593.16
## result.2 104271.15 103846.87 105530.39 105481.08 104844.56 105029.33 104722.20
## result.3 96965.17 97077.32 96720.72 96528.84 98316.99 98437.68 89237.62
## result.4 97738.31 98686.57 98965.48 99200.17 99422.11 99362.97 99531.90
## result.5 99587.35 99248.19 99436.88 99203.38 98555.59 98604.48 98566.14
## result.6 100805.40 100960.95 101384.94 101173.91 101048.83 101280.88 98424.83
##      [,15]      [,16]      [,17]      [,18]      [,19]      [,20]
## result.1 102654.96 103237.23 102274.22 102966.53 103266.27 103131.31
## result.2 104994.94 105951.37 107851.89 108307.62 107479.16 107110.46
## result.3 89893.93 89517.27 90184.42 90413.30 88739.21 89362.95
## result.4 99970.25 100129.70 99076.99 98685.78 98473.30 98130.60
## result.5 96899.66 95792.26 95511.20 95877.52 95719.85 95476.78
## result.6 96374.63 97694.01 98248.22 98374.32 99961.87 100232.91

hist(medium_sim[,n_days], 25)

```

### Histogram of medium\_sim[, n\_days]



```

mean(medium_sim[,n_days])

## [1] 101356.8

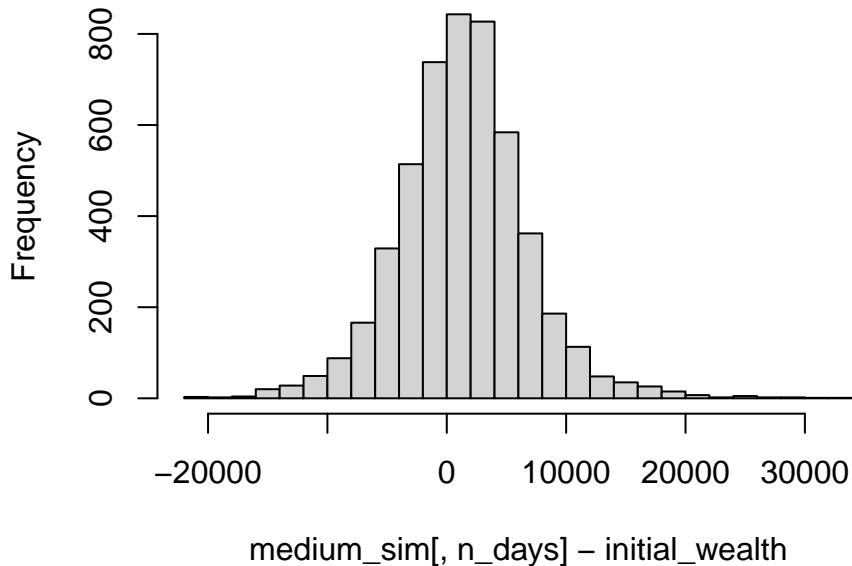
mean(medium_sim[,n_days] - initial_wealth)

## [1] 1356.775

```

```
hist(medium_sim[,n_days] - initial_wealth, breaks=30)
```

## Histogram of medium\_sim[, n\_days] – initial\_wealth



```
# 5% value at risk:  
quantile(medium_sim[,n_days] - initial_wealth, prob=0.05)
```

```
##      5%  
## -7085.436
```

As we suspected, the returns did exceed the safe portfolio created in the first iteration. In fact, the mean returns, \$1318.80 far exceeded the returns of the initial portfolio.

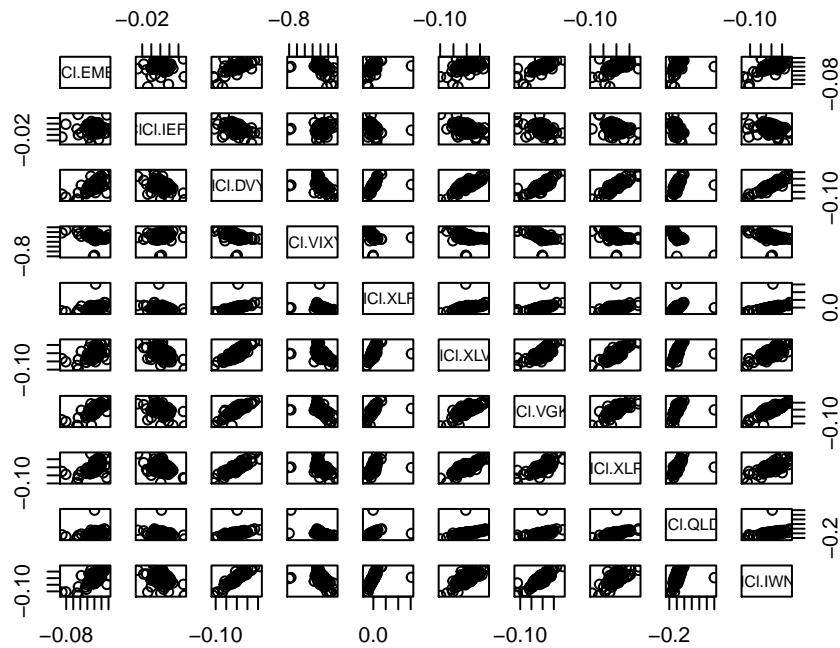
However, the VaR of this portfolio, -\$7398.02 also exceeds the first portfolio. Considering the aggressive additions for this portfolio, that is not completely surprising, but it doesn't back up our hypothesis that additional securities, even aggressive securities, would reduce the overall risk of the portfolio. It should be noted of course that our distribution is centered around slightly positive returns, which means on average an investor can expect positive returns from this portfolio.

```
##Selecting the Final Portfolio
```

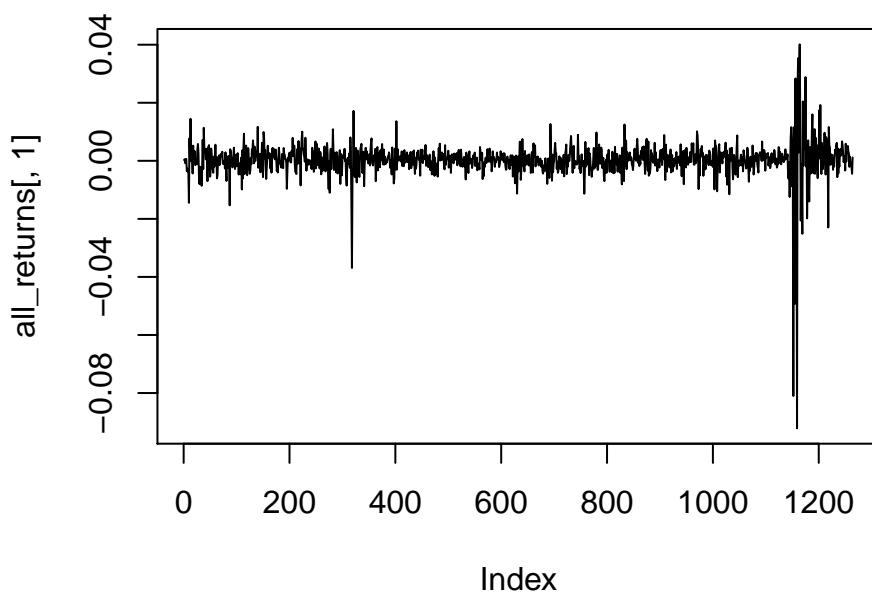
For the final portfolio, we added all of the rest of our securities.

```
#Bind first row into return matrix  
all_returns = cbind(C1C1(EMBa), C1C1(IEFa), C1C1(DVY), C1C1(VIXY), C1C1(XLFA),  
C1C1(XLVA), C1C1(VGKA), C1C1(XLPA), C1C1(QLDA), C1C1(IWNA))  
  
#Get rid of NA first row  
all_returns = as.matrix(na.omit(all_returns))  
N = nrow(all_returns)
```

```
#plots pairs and historical returns  
pairs(all_returns)
```



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



```

initial_wealth = 100000
my_weights3 = c(.1,.1,.1,.1,.1,.1,.1,.1,.1)

set.seed(1234)

big_sim = foreach(i=1:5000, .combine='rbind') %do% {
  total_wealth = initial_wealth
  weights = my_weights3
  holdings = my_weights3*total_wealth
  n_days = 20
  wealthtracker = rep(0,n_days)
  for(today in 1:n_days) {
    return.today = resample(all_returns,1,orig.ids=FALSE)
    holdings = weights*total_wealth
    holdings = holdings*(1+return.today)
    total_wealth = sum(holdings)
    holdings = weights*total_wealth
    wealthtracker[today] = total_wealth
  }
  wealthtracker
}

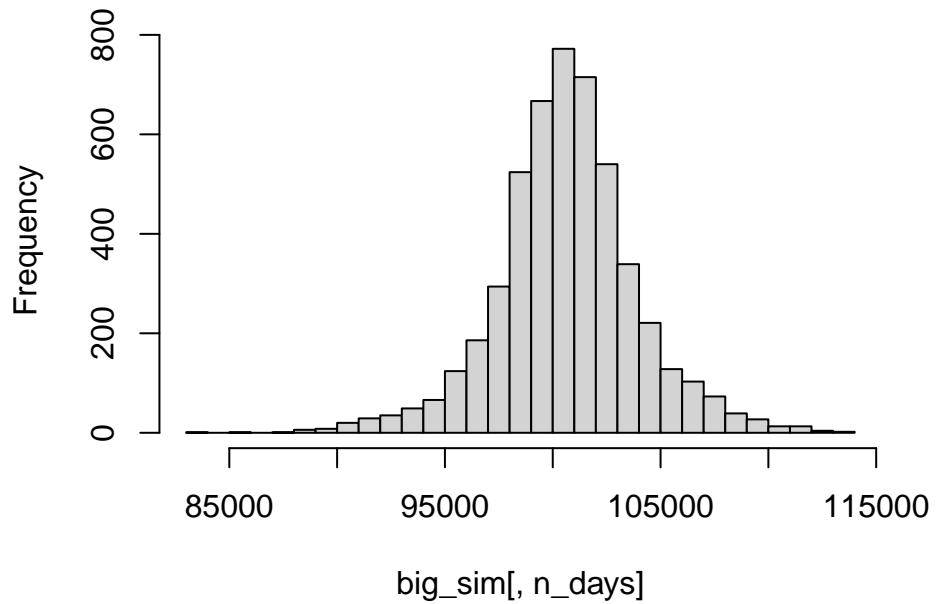
head(big_sim)

##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## result.1 100584.51 100522.67 100853.37 100329.40 100713.93 100881.77 101053.60
## result.2 100299.75 99962.32 100476.47 100198.70 100320.72 100251.82 100677.58
## result.3 100009.31 100751.23 100615.56 100841.19 97841.32 98034.57 98115.57
## result.4 99847.39 99610.87 99597.89 99283.37 99328.66 99762.15 99490.62
## result.5 99564.00 99387.72 99232.71 99309.53 99107.16 99225.45 99317.19
## result.6 99822.94 100160.97 100513.66 100017.05 99740.71 99475.58 99572.79
##          [,8]      [,9]      [,10]     [,11]     [,12]     [,13]     [,14]
## result.1 100961.94 100994.32 101670.74 101519.87 101352.28 101623.60 101950.60
## result.2 100654.12 100348.18 101258.42 101307.92 100904.08 100884.46 100934.76
## result.3 98431.35 98398.19 98276.85 98005.31 99001.46 99046.83 93077.88
## result.4 99522.46 99985.71 100253.37 100324.26 100385.43 100254.14 100537.52
## result.5 99374.69 99320.76 99463.03 99248.31 99303.94 98948.46 98957.64
## result.6 99482.47 99555.36 99868.58 99888.97 100091.95 100174.60 98751.03
##          [,15]     [,16]     [,17]     [,18]     [,19]     [,20]
## result.1 102038.61 102223.12 101902.87 102269.54 102585.61 102597.70
## result.2 100873.63 101319.69 102741.73 102771.76 102870.73 102775.48
## result.3 93357.42 93238.43 93356.13 93279.14 92495.69 92888.64
## result.4 100509.70 100422.06 99925.90 99674.65 99401.97 99522.90
## result.5 98080.06 98010.85 98132.28 98301.25 98234.14 98161.05
## result.6 98228.29 98858.54 99330.65 99526.06 100401.72 100416.04

hist(big_sim[,n_days], 25)

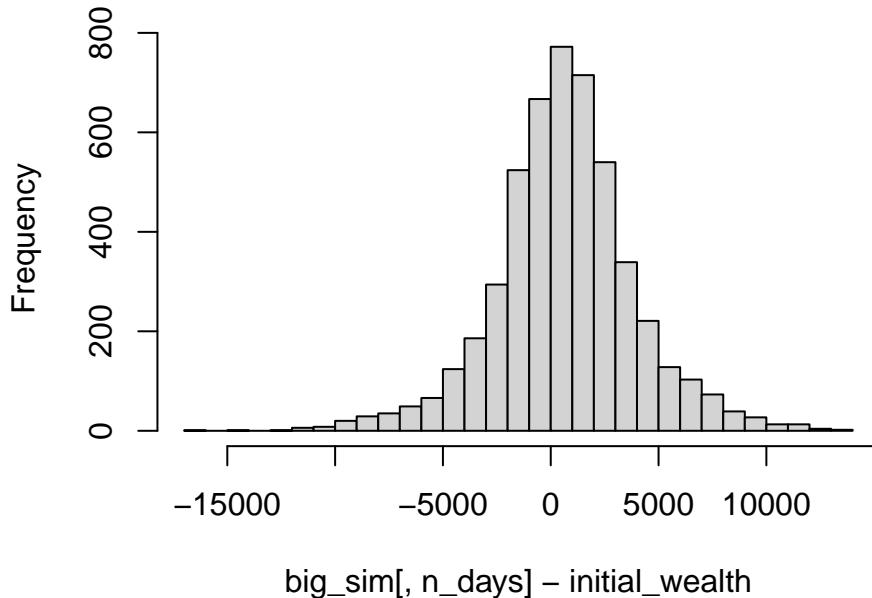
```

### Histogram of big\_sim[, n\_days]



```
mean(big_sim[,n_days])  
## [1] 100638.4  
mean(big_sim[,n_days] - initial_wealth)  
## [1] 638.4383  
hist(big_sim[,n_days] - initial_wealth, breaks=30)
```

## Histogram of big\_sim[, n\_days] – initial\_wealth



```
# 5% value at risk:  
quantile(big_sim[,n_days] - initial_wealth, prob=0.05)  
  
##      5%  
## -4612.515
```

The results of our final portfolio provide the most interesting information. One, or several, of the securities added to our six security portfolio essentially erased some of the returns from our six security portfolio. On the other hand, our VaR was also reduced significantly. It should be noted of course that our distribution is centered around slightly positive returns, which means on average an investor can expect positive returns from this portfolio.

In fact, this portfolio created returns above the initial 3 stock portfolio, with risk less than the 6 stock portfolio. This generally follows the theory that higher returns result in higher risk. However, the higher risk associated with adding 7 additional securities to the intial portfolio is not significantly higher, which may show that we successfully diversified while increasing returns. This is certainly not conclusive, but a strong step towards creating an effective portfolio of ETFs.

## Question 4 - Market Segmentation

NutrientH2O has requested a market segment analysis on their social media audience. We are given 7,882 twitter followers along with the frequency with which they've tweeted about 36 different topics.

From a basic sweep over the various topics, one might assume that some are more correlated than others. For instance, those tweeting about Health and Nutrition are likely to be the same people tweeting about personal fitness. However, given the multitude of possible groupings of these topics, we will want to automate the process. For that, we conduct a k-means clustering analysis. While most of the topics are relevant, we have removed the “chatter” and “uncategorized” topics from our topic list as they appear to have been used by annotators to classify tweets that didn’t fit into other categories. They likely represent a multitude of topics

so we omit them to avoid the k-means model assuming that they represent one topic.

To choose the optimal number of clusters, we first look at the Gap Statistic for various values of k.

```
## 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
## 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
## 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
## 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: Quick-TRANSfer stage steps exceeded maximum (= 394100)
## Warning: did not converge in 10 iterations
```









```
## 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: 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: Quick-TRANSfer stage steps exceeded maximum (= 394100)
## Warning: Quick-TRANSfer stage steps exceeded maximum (= 394100)
## Warning: did not converge in 10 iterations
```

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

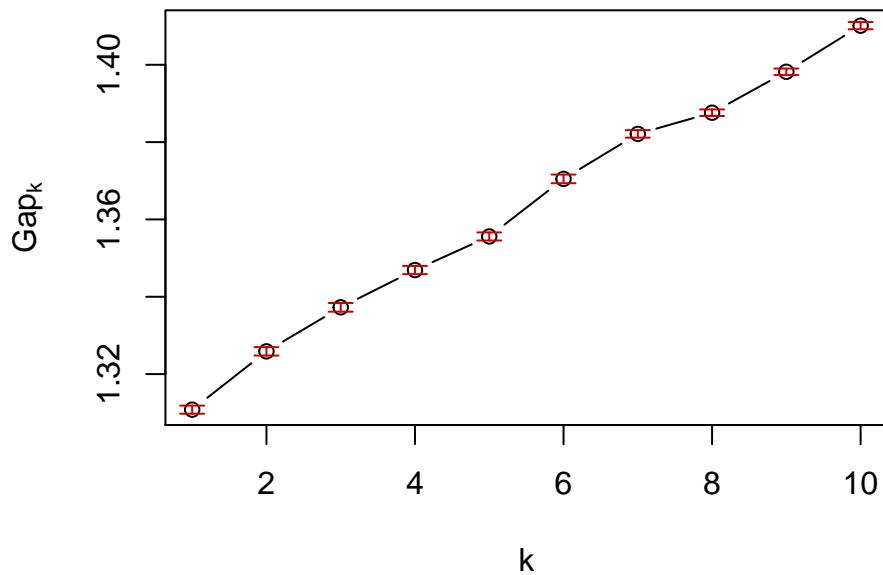
```
## Warning: did not converge in 10 iterations
```

```

## Warning: did not converge in 10 iterations

```

## Gap Statistic vs. Number of Clusters



With no clear kinks in this gap statistic plot, we are not getting a clear definition of what number of clusters to choose, and the data is not converging cleanly before  $k = 10$ . However, we decide to choose 5 clusters to hopefully identify easily interpretable market segments within the NutrientH2O social media following.

Now we can construct our k-means clustering with  $k=5$  and 25 initial configurations. The k-means algorithm clusters by the following percentages (we will look at the characteristics of these clusters shortly):

- Group 1 - 61.38% of twitter following
- Group 2 - 9.99% of twitter following
- Group 3 - 9.07% of twitter following
- Group 4 - 7.66% of twitter following
- Group 5 - 11.89% of twitter following

After automating the market segment split via kmeans, we confirm our cluster choices by conducting a k-means++ initialization and comparing the centroids of our clusters from each initialization method.

Within-cluster average distances for the first run are identical for k-means and k-means++ after 25 iterations.

Kmeans average distances:

```
## [1] 23839.26 27831.82 30402.61 30656.29 96126.34
```

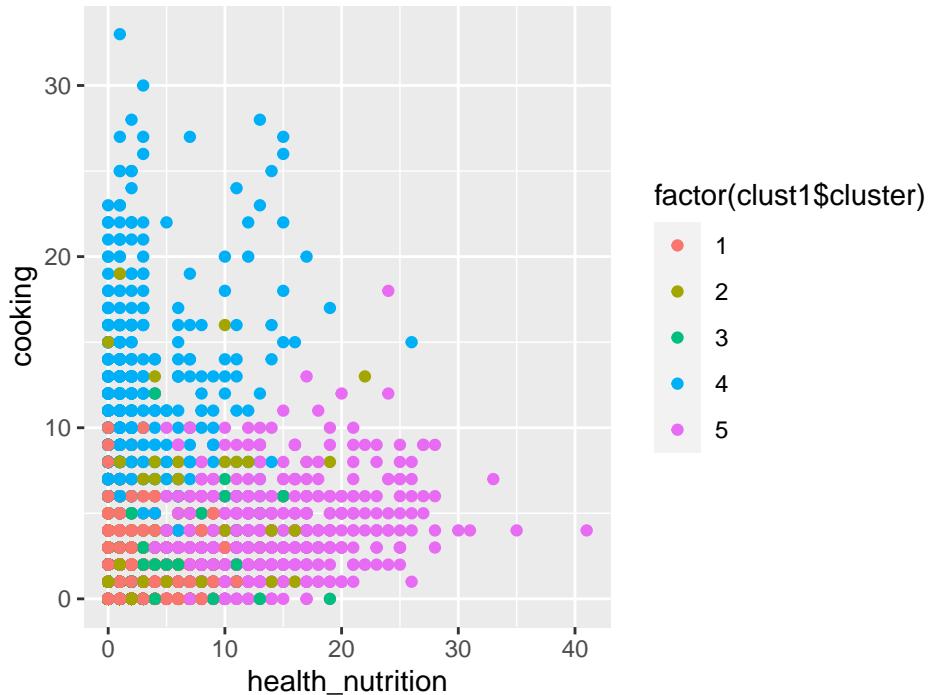
K-means++ average distances:

```
## [1] 23839.26 27831.82 30402.61 30656.29 96126.34
```

We can see that from both k-means and k-means++ initialization, we receive identical groups for our 5 clusters.

Having established five different market segments, we can explore the characteristics of each segment visually through a few topic comparison plots.

### Interest in Health vs. Cooking for Different Market Segments



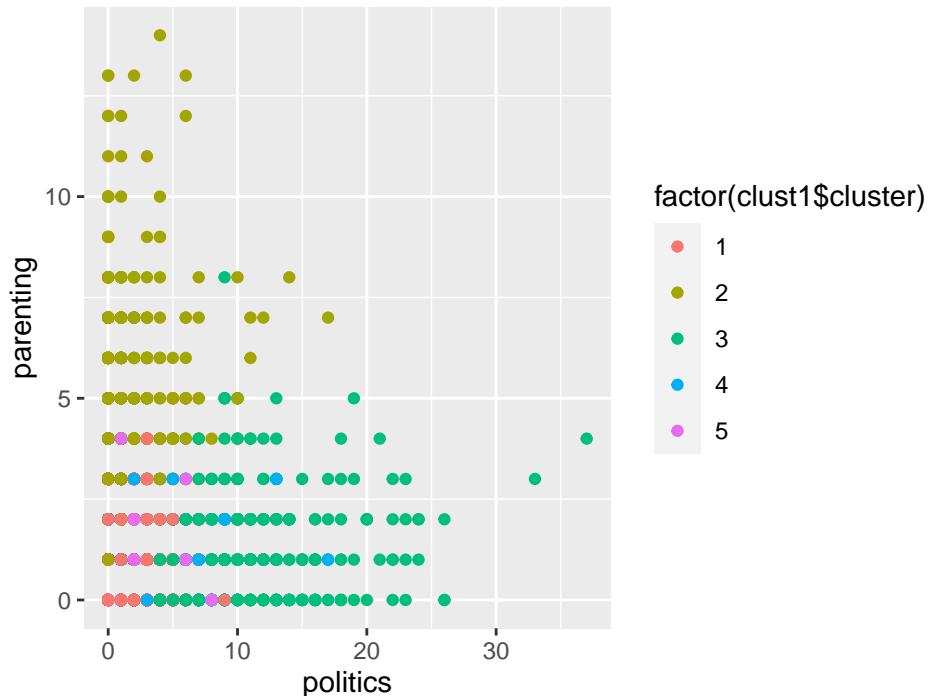
Here we see an interesting split between clusters - although group 5 seems to care greatly about health and nutrition, they care less about cooking than does group 4. This gives us the inkling that group 5 might be our “fit” group.

## Interest in Health vs. Politics for Different Market Segments

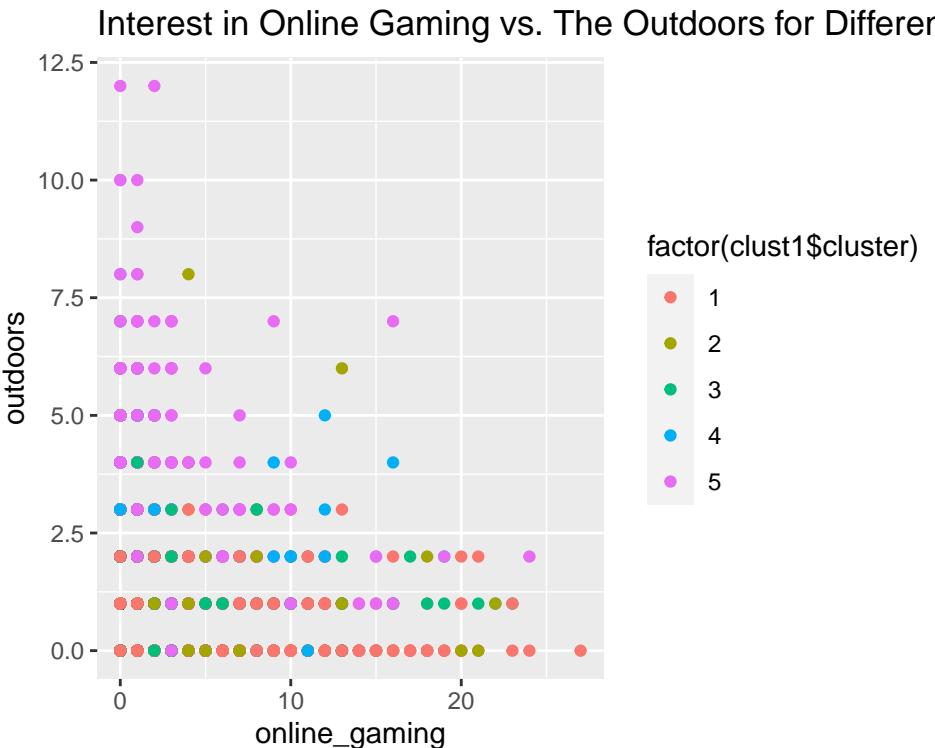


Here we can see that group 3 concerns themselves with politics far more often than do the other twitter followers.

## Interest in Politics vs. Parenting for Different Market Segments



Here we can see that group 2 is more concerned with parenting than any other group. This might be a more family-oriented audience.



Finally, here we again see that our “fit” group - group 5- is the most interested in the outdoors, while group 1 stands out as having interests in online gaming.

Thus, we can see some distinct characteristics about each cluster of NutrientH20 twitter followers. We can look at the top 5 defining topics for the centroids of each cluster to start to develop a better idea of who falls into each group.

### “The General Public”

```
## photo_sharing college_uni current_events shopping online_gaming
##      2.311906     1.511782     1.449153     1.269740     1.168458
```

Group 1 tends to share photos and post about online gaming, college, and shopping at higher rates than other groups. However, none of the topics stand out with a particularly high importance. It appears k-means has defined this cluster as a “catch-all” for individuals who don’t fit the four molds described below.

### "Family-Oriented"

```
## sports_fandom religion food parenting school
##      5.864213     5.241117     4.535533     4.016497     2.687817
```

Group 2 concerns themselves with sports fandom, religion, food and family topics. We might assume this to be middle-aged parents and a generally more family-oriented audience.

### “Internationally Aware”

```
## politics travel news photo_sharing computers
##      8.823776     5.566434     5.195804     2.514685     2.467133
```

Group 3 posts frequently about politics, news, and travel. These might be internationally inclined, exploratory individuals.

## “The Insta Girls”

```
##          cooking    photo_sharing      fashion      beauty
##        10.607616       6.082781       5.480132      3.804636
## health_nutrition
##        2.271523
```

Group 4 tends to frequently share photos and concern themselves with cooking, fashion, and beauty.

## “The Fit-Focused”

```
## health_nutrition personal_fitness      cooking    photo_sharing
##        11.843116       6.354322       3.252935      2.704376
##     outdoors
##        2.672359
```

Group 5 posts are very much focused on health, nutrition, fitness, and to a lesser extent the outdoors. This may very well be NutrientH20’s target market.

Given NutrientH20’s branding, we might assume some interest in the seemingly health and fitness-focused market segment that is group 5. Below we have compiled the 937 “group 3” members that tend to be health, nutrition, and fitness inclined. We display the first five user codes as an example.

```
## [1] "hmjoe4g3k" "y2g68vhkf" "4odi1h6wq" "qg1jsawuy" "af7eqjw8r" "p94myqeo6"
```

Without full information on its marketing strategy, we cannot be certain as to which consumers NutrientH20 wishes to target. However, we suspect that the “Fit-Focused” group, as characterized above by interests in health and personal fitness, might be the most receptive of Nutrient H20’s marketing material. We should note that this demographic only makes up 12% of NutrientH20’s Twitter following, and still might find value in marketing to “The General Public” (61% of following) or “The Insta Girls” (8% of following).

We hope this has helped NutrientH20 identify its target market among its twitter followers and be able to target advertising to this group of customers more effectively.

## Question 5 - Author Attribution

### Step 1:

The first step to predicting the author of a given text is to create the train set from the C50Train set:

```
library(tm)
```

```
## Loading required package: NLP
##
## Attaching package: 'NLP'
##
## The following object is masked from 'package:ggplot2':
## 
##     annotate
##
## Attaching package: 'tm'
##
## The following object is masked from 'package:arules':
## 
##     inspect
##
## The following object is masked from 'package:mosaic':
## 
```

```

##      inspect
library(magrittr)

##
## Attaching package: 'magrittr'
## The following object is masked from 'package:purrr':
##
##      set_names

## The following object is masked from 'package:tidyverse':
##
##      extract

library(slam)
library(proxy)

## Registered S3 methods overwritten by 'proxy':
##   method           from
##   print.registry_field registry
##   print.registry_entry registry

##
## Attaching package: 'proxy'
## The following object is masked from 'package:Matrix':
##
##      as.matrix

## The following objects are masked from 'package:stats':
##
##      as.dist, dist

## The following object is masked from 'package:base':
##
##      as.matrix

library(caret)

##
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
##      lift

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

library(plyr)

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

```

## Attaching package: 'plyr'
## The following object is masked from 'package:purrr':
##   compact
## The following object is masked from 'package:mosaic':
##   count
## The following objects are masked from 'package:dplyr':
##   arrange, count, desc, failwith, id, mutate, rename, summarise,
##   summarise
library(dplyr)
library(ggplot2)
library('e1071')
library(randomForest)

## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##   margin
## The following object is masked from 'package:dplyr':
##   combine
library(ggplot2)
library(class)

train=Sys.glob('C:/Users/Christian/Documents/UT MSBA/Predictive Modelling/C50train/*')

#Creating training dataset
authortrain=NULL
labels=NULL

for (name in train)
{
  author=substring(name,first=50)
  article=Sys.glob(paste0(name,'/*.txt'))
  authortrain=append(authortrain,article)
  labels=append(labels,rep(author,length(article)))
}

readerPlain <- function(fname)
{
  readPlain(elem=list(content=readLines(fname)),
            id=fname, language='en')
}

```

```

comb = lapply(authortrain, readerPlain)
names(comb) = authortrain
names(comb) = sub('.txt', '', names(comb))

corp_train=Corpus(VectorSource(comb))

```

## Step 2:

The next thing that we need to do is wrangle the data a bit to make the text comparable across files and remove any numbers or characters that might offset the models.

The second part of this step is to create our Document Term Matrix and then our TF-IDF matrix so that we can assess the number of occurrences of a particular word in any given document and across all documents.

```
corp_train = tm_map(corp_train, content_transformer(tolower))
```

```
## Warning in tm_map.SimpleCorpus(corp_train, content_transformer(tolower)):
## transformation drops documents
```

```
corp_train = tm_map(corp_train, content_transformer(removeNumbers))
```

```
## Warning in tm_map.SimpleCorpus(corp_train, content_transformer(removeNumbers)):
## transformation drops documents
```

```
corp_train = tm_map(corp_train, content_transformer(removePunctuation))
```

```
## Warning in tm_map.SimpleCorpus(corp_train,
## content_transformer(removePunctuation)): transformation drops documents
```

```
corp_train = tm_map(corp_train, content_transformer(stripWhitespace))
```

```
## Warning in tm_map.SimpleCorpus(corp_train,
## content_transformer(stripWhitespace)): transformation drops documents
```

```
corp_train = tm_map(corp_train, content_transformer(removeWords), stopwords("en"))
```

```
## Warning in tm_map.SimpleCorpus(corp_train, content_transformer(removeWords), :
## transformation drops documents
```

```
DTM_train = DocumentTermMatrix(corp_train)
```

```
DTM_train
```

```
## <<DocumentTermMatrix (documents: 2500, terms: 32572)>>
```

```
## Non-/sparse entries: 542861/80887139
```

```
## Sparsity : 99%
```

```
## Maximal term length: 41
```

```
## Weighting : term frequency (tf)
```

```
DTM_tr=removeSparseTerms(DTM_train,.99)
```

```
tf_idf = weightTfIdf(DTM_tr)
```

```
DTM_train<-as.matrix(tf_idf)
```

```
tf_idf
```

```
## <<DocumentTermMatrix (documents: 2500, terms: 3395)>>
```

```
## Non-/sparse entries: 382971/8104529
```

```
## Sparsity : 95%
```

```
## Maximal term length: 41
```

```

## Weighting          : term frequency - inverse document frequency (normalized) (tf-idf)

```

**Step 3:**

Do the same with the test data:

```

test=Sys.glob('C:/Users/Christian/Documents/UT MSBA/Predictive Modelling/C50test/*')

authortest=NULL
labels1=NULL

for (name in test)
{
  author1=substring(name,first=50)
  article1=Sys.glob(paste0(name,'*.txt'))
  authortest=append(authortest,article1)
  labels1=append(labels1,rep(author1,length(article1)))
}

comb1 = lapply(authortest, readerPlain)
names(comb1) = authortest
names(comb1) = sub('.txt', '', names(comb1))

corp_test=Corpus(VectorSource(comb1))

corp_test = tm_map(corp_test, content_transformer(tolower))

## Warning in tm_map.SimpleCorpus(corp_test, content_transformer(tolower)):
## transformation drops documents
corp_test = tm_map(corp_test, content_transformer(removeNumbers))

## Warning in tm_map.SimpleCorpus(corp_test, content_transformer(removeNumbers)):
## transformation drops documents
corp_test = tm_map(corp_test, content_transformer(removePunctuation))

## Warning in tm_map.SimpleCorpus(corp_test,
## content_transformer(removePunctuation)): transformation drops documents
corp_test = tm_map(corp_test, content_transformer(stripWhitespace))

## Warning in tm_map.SimpleCorpus(corp_test, content_transformer(stripWhitespace)):
## transformation drops documents
corp_test = tm_map(corp_test, content_transformer(removeWords),stopwords("en"))

## Warning in tm_map.SimpleCorpus(corp_test, content_transformer(removeWords), :
## transformation drops documents
DTM_tst=DocumentTermMatrix(corp_test,list(dictionary=colnames(DTM_tr)))
tf_idf_tests = weightTfIdf(DTM_tst)

## Warning in weightTfIdf(DTM_tst): unreferenced term(s):
## modellingctrainaaaronpressmannewsmltxt modellingctrainalancrosbynewsmltxt

```

```

## modellingctrainalexandersmithnewsmltxt modellingctrainbenjaminkanglimnewsmltxt
## modellingctrainbernardhickeynewsmltxt modellingctrainbraddorfmannewsmltxt
## modellingctraindarrenschuettlernewsmltxt modellingctraindavidlawdernewsmltxt
## modellingctrainednafernandesnewsmltxt modellingctrainericauchardnewsmltxt
## modellingctrainfumikofujisakinewsmltxt modellingctrainingrahamearnshawnewsmltxt
## modellingctrainheatherscoffieldnewsmltxt modellingctrainjanlopatkanewsmltxt
## modellingctrainjanemacartneynewsmltxt modellingctrainjimgilchristnewsmltxt
## modellingctrainjowinterbottomnewsmltxt modellingctrainjoeortiznewsmltxt
## modellingctrainjohnmastrininewsmltxt modellingctrainjonathanbirtnewsmltxt
## modellingctrainkarlpenhaulnewsmltxt modellingctrainkeithweirnewsmltxt
## modellingctrainkevindrawbaughnewsmltxt modellingctrainkevinmorrisonnewsmltxt
## modellingctrainkirstinridleynewsmltxt modellingctrainkouroshkarimkhanynewsmltxt
## modellingctrainlydiazacajcnewsmltxt modellingctrainlynneodonnellnewsmltxt
## modellingctrainlynleybrowningnewsmltxt modellingctrainmarcelmichelsonnewsmltxt
## modellingctrainmarkbendeichnewsmltxt modellingctrainmartinwolknewsmltxt
## modellingctrainmatthewbuncenewsmltxt modellingctrainmichaelconnornewsmltxt
## modellingctrainmuredickienewsmltxt modellingctrainnicklouthnewsmltxt
## modellingctrainpatrickacomminsnewsmltxt modellingctrainpeterhumphreynewsmltxt
## modellingctrainpierretrannewsmltxt modellingctrainrobinsidelnewsmltxt
## modellingctrainsarahdavisonnewsmltxt modellingctrainscotthillisnewsmltxt
## modellingctrainsimoncowellnewsmltxt modellingctraintaneelynnewsmltxt
## modellingctraintheresepolettinewsmltxt modellingctraintimfarrandnewsmltxt
## modellingctraintoddnissennewsmltxt modellingctrainwilliamkazernewsmltxt

DTM_test<-as.matrix(tf_idf_tests)
tf_idf_tests

## <<DocumentTermMatrix (documents: 2500, terms: 3395)>>
## Non-/sparse entries: 379314/8108186
## Sparsity : 96%
## Maximal term length: 41
## Weighting : term frequency - inverse document frequency (normalized) (tf-idf)

```

Now that we have created our train and test data sets, we need to reduce the dimensionality of our data so that we can apply a PCA analysis. This is related to the “curse of dimensionality” which is a problem because when our data is high dimensional, the models tend to start overfitting the data which leads to high out of sample error.

We then run a PCA using prcomp, scale=True to ensure that our input data has been standardized and has a zero mean and variance of one. We then plot our PCA outcome which shows a reduction in variance. We also need to find how much of the variance can be explained by each component. If we print out the proportion of variance to sum of variances, we see that at PC730 we have about 75% of variance explained by the components.

```

DTM_train1<-DTM_train[,which(colSums(DTM_train) != 0)]
DTM_test1<-DTM_test[,which(colSums(DTM_test) != 0)]

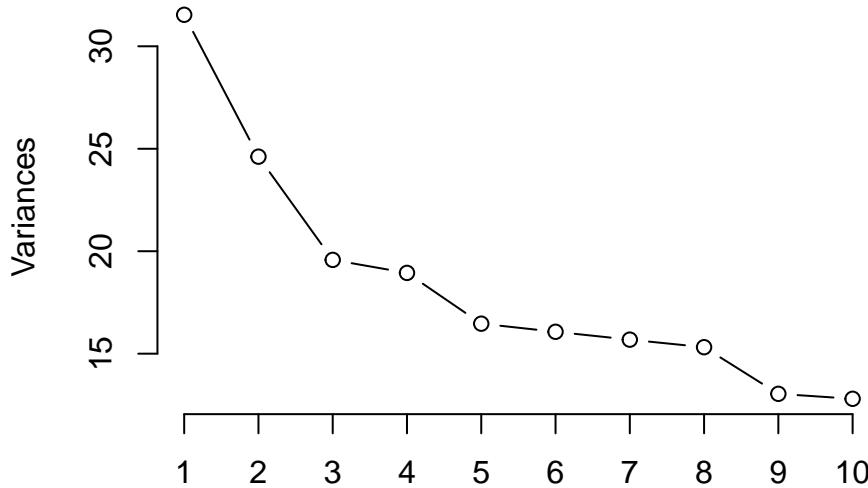
DTM_test1 = DTM_test1[,intersect(colnames(DTM_test1),colnames(DTM_train1))]
DTM_train1 = DTM_train1[,intersect(colnames(DTM_test1),colnames(DTM_train1))]

mod_pca = prcomp(DTM_train1,scale=TRUE)
pred_pca=predict(mod_pca,newdata = DTM_test1)

plot(mod_pca,type='line')

```

## mod\_pca



```
var <- apply(mod_pca$x, 2, var)
prop <- var / sum(var)
cumsum(prop)

##          PC1          PC2          PC3          PC4          PC5          PC6
## 0.009479095 0.016877628 0.022761820 0.028455367 0.033404000 0.038233810
##          PC7          PC8          PC9          PC10         PC11         PC12
## 0.042948219 0.047552109 0.051471990 0.055318969 0.058902425 0.062338432
##          PC13         PC14          PC15          PC16          PC17          PC18
## 0.065673432 0.068957926 0.072033770 0.075067784 0.078061800 0.080917395
##          PC19         PC20          PC21          PC22          PC23          PC24
## 0.083731736 0.086474435 0.089126133 0.091743850 0.094351409 0.096931852
##          PC25         PC26          PC27          PC28          PC29          PC30
## 0.099491097 0.101967086 0.104414891 0.106838750 0.109190550 0.111501594
##          PC31         PC32          PC33          PC34          PC35          PC36
## 0.113793732 0.116045716 0.118265526 0.120466087 0.122634062 0.124783760
##          PC37         PC38          PC39          PC40          PC41          PC42
## 0.126910899 0.129009644 0.131076087 0.133122077 0.135158511 0.137165685
##          PC43         PC44          PC45          PC46          PC47          PC48
## 0.139163086 0.141151843 0.143121313 0.145071606 0.146976444 0.148870374
##          PC49         PC50          PC51          PC52          PC53          PC54
## 0.150755299 0.152624633 0.154484678 0.156334196 0.158178721 0.160004063
##          PC55         PC56          PC57          PC58          PC59          PC60
## 0.161818326 0.163627203 0.165409070 0.167186673 0.168945938 0.170696810
##          PC61         PC62          PC63          PC64          PC65          PC66
## 0.172442699 0.174176534 0.175898114 0.177618009 0.179323692 0.181017078
##          PC67         PC68          PC69          PC70          PC71          PC72
## 0.182695354 0.184363673 0.186024337 0.187683897 0.189333429 0.190981127
##          PC73         PC74          PC75          PC76          PC77          PC78
```

```

## 0.192617224 0.194245216 0.195864624 0.197480624 0.199084826 0.200681120
## PC79      PC80      PC81      PC82      PC83      PC84
## 0.202271907 0.203856480 0.205434195 0.207008458 0.208579343 0.210137522
## PC85      PC86      PC87      PC88      PC89      PC90
## 0.211689618 0.213234863 0.214773338 0.216305930 0.217832990 0.219351109
## PC91      PC92      PC93      PC94      PC95      PC96
## 0.220868076 0.222381416 0.223886219 0.225379815 0.226873030 0.228357379
## PC97      PC98      PC99      PC100     PC101     PC102
## 0.229836167 0.231310251 0.232778140 0.234242558 0.235704150 0.237161285
## PC103     PC104     PC105     PC106     PC107     PC108
## 0.238609851 0.240056907 0.241495977 0.242932536 0.244367392 0.245797406
## PC109     PC110     PC111     PC112     PC113     PC114
## 0.247221644 0.248641440 0.250057820 0.251467213 0.252871416 0.254273537
## PC115     PC116     PC117     PC118     PC119     PC120
## 0.255665537 0.257055487 0.258439869 0.259823038 0.261203216 0.262576989
## PC121     PC122     PC123     PC124     PC125     PC126
## 0.263949648 0.265317615 0.266679961 0.268038133 0.269391758 0.270744190
## PC127     PC128     PC129     PC130     PC131     PC132
## 0.272095199 0.273438503 0.274779883 0.276118807 0.277454749 0.278783499
## PC133     PC134     PC135     PC136     PC137     PC138
## 0.280110914 0.281431815 0.282750472 0.284068034 0.285379301 0.286688321
## PC139     PC140     PC141     PC142     PC143     PC144
## 0.287991801 0.289291227 0.290589417 0.291882250 0.293173735 0.294463775
## PC145     PC146     PC147     PC148     PC149     PC150
## 0.295747933 0.297027319 0.298302619 0.299577067 0.300849159 0.302117852
## PC151     PC152     PC153     PC154     PC155     PC156
## 0.303382876 0.304644887 0.305903898 0.307159565 0.308413367 0.309662569
## PC157     PC158     PC159     PC160     PC161     PC162
## 0.310908236 0.312150264 0.313390155 0.314626279 0.315858274 0.317089463
## PC163     PC164     PC165     PC166     PC167     PC168
## 0.318315336 0.319539551 0.320760321 0.321977906 0.323191907 0.324403621
## PC169     PC170     PC171     PC172     PC173     PC174
## 0.325614165 0.326818656 0.328021552 0.329220602 0.330418991 0.331613609
## PC175     PC176     PC177     PC178     PC179     PC180
## 0.332805167 0.333993229 0.335179933 0.336361186 0.337541040 0.338717731
## PC181     PC182     PC183     PC184     PC185     PC186
## 0.339892047 0.341065532 0.342234619 0.343402911 0.344568857 0.345732929
## PC187     PC188     PC189     PC190     PC191     PC192
## 0.346891653 0.348046059 0.349198767 0.350349477 0.351498578 0.352643619
## PC193     PC194     PC195     PC196     PC197     PC198
## 0.353787875 0.354930412 0.356071967 0.357209324 0.358344185 0.359477832
## PC199     PC200     PC201     PC202     PC203     PC204
## 0.360605970 0.361732731 0.362859378 0.363983727 0.365103589 0.366220848
## PC205     PC206     PC207     PC208     PC209     PC210
## 0.367333572 0.368445090 0.369555752 0.370664165 0.371771478 0.372874896
## PC211     PC212     PC213     PC214     PC215     PC216
## 0.373976968 0.375077967 0.376176299 0.377271439 0.378364798 0.379457219
## PC217     PC218     PC219     PC220     PC221     PC222
## 0.380545196 0.381632276 0.382715524 0.383796961 0.384875186 0.385951129
## PC223     PC224     PC225     PC226     PC227     PC228
## 0.387025370 0.388097351 0.389168342 0.390237362 0.391305673 0.392372282
## PC229     PC230     PC231     PC232     PC233     PC234
## 0.393435807 0.394497449 0.395558375 0.396615904 0.397670913 0.398724214
## PC235     PC236     PC237     PC238     PC239     PC240

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## 0.399774591 0.400820057 0.401864988 0.402908814 0.403950546 0.404989074
## PC241      PC242      PC243      PC244      PC245      PC246
## 0.406025205 0.407059856 0.408092258 0.409122788 0.410149609 0.411175269
## PC247      PC248      PC249      PC250      PC251      PC252
## 0.412198675 0.413218808 0.414237722 0.415255474 0.416271794 0.417287057
## PC253      PC254      PC255      PC256      PC257      PC258
## 0.418300955 0.419313087 0.420323326 0.421330178 0.422335418 0.423338929
## PC259      PC260      PC261      PC262      PC263      PC264
## 0.424339320 0.425337366 0.426334166 0.427328665 0.428321215 0.429312721
## PC265      PC266      PC267      PC268      PC269      PC270
## 0.430301963 0.431290637 0.432277505 0.433261741 0.434243074 0.435223243
## PC271      PC272      PC273      PC274      PC275      PC276
## 0.436202043 0.437179145 0.438154237 0.439127506 0.440098518 0.441068704
## PC277      PC278      PC279      PC280      PC281      PC282
## 0.442035513 0.442998544 0.443960956 0.444922037 0.445881958 0.446841178
## PC283      PC284      PC285      PC286      PC287      PC288
## 0.447798773 0.448754931 0.449708359 0.450660294 0.451611449 0.452559781
## PC289      PC290      PC291      PC292      PC293      PC294
## 0.453507335 0.454454369 0.455399715 0.456342416 0.457284213 0.458223378
## PC295      PC296      PC297      PC298      PC299      PC300
## 0.459160463 0.460094515 0.461026156 0.461957492 0.462886723 0.463814576
## PC301      PC302      PC303      PC304      PC305      PC306
## 0.464741493 0.465667309 0.466591273 0.467514202 0.468435191 0.469353247
## PC307      PC308      PC309      PC310      PC311      PC312
## 0.470270475 0.471185515 0.472098631 0.473010935 0.473920012 0.474828119
## PC313      PC314      PC315      PC316      PC317      PC318
## 0.475735509 0.476641815 0.477547766 0.478451000 0.479352256 0.480251571
## PC319      PC320      PC321      PC322      PC323      PC324
## 0.481150490 0.482047184 0.482943568 0.483838671 0.484732430 0.485623104
## PC325      PC326      PC327      PC328      PC329      PC330
## 0.486512576 0.487400095 0.488287177 0.489173330 0.490057113 0.490938905
## PC331      PC332      PC333      PC334      PC335      PC336
## 0.491819773 0.492698882 0.493577054 0.494453077 0.495327797 0.496199038
## PC337      PC338      PC339      PC340      PC341      PC342
## 0.497069330 0.497938386 0.498806342 0.499673219 0.500539513 0.501404464
## PC343      PC344      PC345      PC346      PC347      PC348
## 0.502267345 0.503128318 0.503988475 0.504845375 0.505701223 0.506556958
## PC349      PC350      PC351      PC352      PC353      PC354
## 0.507410776 0.508262021 0.509112512 0.509961168 0.510808092 0.511653500
## PC355      PC356      PC357      PC358      PC359      PC360
## 0.512498113 0.513341190 0.514183048 0.515022316 0.515861371 0.516696779
## PC361      PC362      PC363      PC364      PC365      PC366
## 0.517531625 0.518364571 0.519196027 0.520027103 0.520857123 0.521685932
## PC367      PC368      PC369      PC370      PC371      PC372
## 0.522512310 0.523338583 0.524162920 0.524985169 0.525804513 0.526623591
## PC373      PC374      PC375      PC376      PC377      PC378
## 0.527440740 0.528257051 0.529072064 0.529885732 0.530699117 0.531511474
## PC379      PC380      PC381      PC382      PC383      PC384
## 0.532322266 0.533132508 0.533939504 0.534744984 0.535549683 0.536352366
## PC385      PC386      PC387      PC388      PC389      PC390
## 0.537154100 0.537955214 0.538754618 0.539553114 0.540350919 0.541147461
## PC391      PC392      PC393      PC394      PC395      PC396
## 0.541940819 0.542733143 0.543524960 0.544314586 0.545102770 0.545889993
## PC397      PC398      PC399      PC400      PC401      PC402

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## 0.546676524 0.547461482 0.548246114 0.549029292 0.549810830 0.550591289
## PC403      PC404      PC405      PC406      PC407      PC408
## 0.551369881 0.552147774 0.552923045 0.553697734 0.554472056 0.555245803
## PC409      PC410      PC411      PC412      PC413      PC414
## 0.556018232 0.556788434 0.557557834 0.558325245 0.559092079 0.559858507
## PC415      PC416      PC417      PC418      PC419      PC420
## 0.560623611 0.561388274 0.562151240 0.562913484 0.563674135 0.564433261
## PC421      PC422      PC423      PC424      PC425      PC426
## 0.565190778 0.565947052 0.566703004 0.567455391 0.568206962 0.568957749
## PC427      PC428      PC429      PC430      PC431      PC432
## 0.569706608 0.570454533 0.571201755 0.571946876 0.572691310 0.573435250
## PC433      PC434      PC435      PC436      PC437      PC438
## 0.574177297 0.574918610 0.575659030 0.576398029 0.577136093 0.577873343
## PC439      PC440      PC441      PC442      PC443      PC444
## 0.578608913 0.579344207 0.580078084 0.580810443 0.581541879 0.582272789
## PC445      PC446      PC447      PC448      PC449      PC450
## 0.583002659 0.583730458 0.584457762 0.585184298 0.585909113 0.586632010
## PC451      PC452      PC453      PC454      PC455      PC456
## 0.587354610 0.588075998 0.588795819 0.589515227 0.590233555 0.590950867
## PC457      PC458      PC459      PC460      PC461      PC462
## 0.591666793 0.592380216 0.593092717 0.593804894 0.594515339 0.595224481
## PC463      PC464      PC465      PC466      PC467      PC468
## 0.595931593 0.596638143 0.597343899 0.598048038 0.598751362 0.599453790
## PC469      PC470      PC471      PC472      PC473      PC474
## 0.600154696 0.600854806 0.601554344 0.602251286 0.602947099 0.603642078
## PC475      PC476      PC477      PC478      PC479      PC480
## 0.604336943 0.605030228 0.605723173 0.606414055 0.607104418 0.607793715
## PC481      PC482      PC483      PC484      PC485      PC486
## 0.608481418 0.609168688 0.609854702 0.610540365 0.611224295 0.611906239
## PC487      PC488      PC489      PC490      PC491      PC492
## 0.612587229 0.613267711 0.613945699 0.614622724 0.615299406 0.615974893
## PC493      PC494      PC495      PC496      PC497      PC498
## 0.616649843 0.617322729 0.617994763 0.618666467 0.619338022 0.620006738
## PC499      PC500      PC501      PC502      PC503      PC504
## 0.620675045 0.621342134 0.622008429 0.622672804 0.623336064 0.623999026
## PC505      PC506      PC507      PC508      PC509      PC510
## 0.624661399 0.625322613 0.625982796 0.626640864 0.627298479 0.627955001
## PC511      PC512      PC513      PC514      PC515      PC516
## 0.628611480 0.629265408 0.629918502 0.630571148 0.631222857 0.631873389
## PC517      PC518      PC519      PC520      PC521      PC522
## 0.632522768 0.633171913 0.633819781 0.634466982 0.635113392 0.635757959
## PC523      PC524      PC525      PC526      PC527      PC528
## 0.636401465 0.637044624 0.637686851 0.638327934 0.638968505 0.639607262
## PC529      PC530      PC531      PC532      PC533      PC534
## 0.640245260 0.640881621 0.641516662 0.642150937 0.642783584 0.643415763
## PC535      PC536      PC537      PC538      PC539      PC540
## 0.644047632 0.644678422 0.645309061 0.645938387 0.646566799 0.647194799
## PC541      PC542      PC543      PC544      PC545      PC546
## 0.647820985 0.648445572 0.649069478 0.649692045 0.650314463 0.650936210
## PC547      PC548      PC549      PC550      PC551      PC552
## 0.651556329 0.652175820 0.652794207 0.653412350 0.654028338 0.654643904
## PC553      PC554      PC555      PC556      PC557      PC558
## 0.655258785 0.655872826 0.656485324 0.657096950 0.657707794 0.658318295
## PC559      PC560      PC561      PC562      PC563      PC564

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## 0.658927637 0.659536172 0.660144597 0.660752080 0.661358549 0.661963891
## PC565      PC566      PC567      PC568      PC569      PC570
## 0.662567522 0.663170367 0.663772787 0.664373906 0.664974130 0.665572956
## PC571      PC572      PC573      PC574      PC575      PC576
## 0.666171462 0.666768400 0.667364955 0.667960376 0.668555366 0.669149733
## PC577      PC578      PC579      PC580      PC581      PC582
## 0.669742348 0.670334721 0.670925299 0.671515198 0.672104217 0.672692594
## PC583      PC584      PC585      PC586      PC587      PC588
## 0.673279946 0.673866705 0.674452799 0.675037084 0.675621027 0.676204269
## PC589      PC590      PC591      PC592      PC593      PC594
## 0.676785714 0.677366149 0.677944756 0.678522723 0.679100358 0.679677066
## PC595      PC596      PC597      PC598      PC599      PC600
## 0.680253177 0.680828735 0.681403354 0.681976948 0.682550405 0.683122656
## PC601      PC602      PC603      PC604      PC605      PC606
## 0.683693926 0.684264557 0.684834936 0.685404716 0.685972401 0.686539840
## PC607      PC608      PC609      PC610      PC611      PC612
## 0.687106833 0.687672783 0.688237186 0.688800431 0.689363235 0.689924969
## PC613      PC614      PC615      PC616      PC617      PC618
## 0.690485841 0.691045446 0.691604413 0.692162297 0.692719421 0.693275264
## PC619      PC620      PC621      PC622      PC623      PC624
## 0.693830812 0.694386245 0.694940017 0.695492811 0.696044835 0.696596132
## PC625      PC626      PC627      PC628      PC629      PC630
## 0.697147092 0.697696743 0.698245397 0.698793321 0.699340902 0.699888007
## PC631      PC632      PC633      PC634      PC635      PC636
## 0.700434342 0.700979872 0.701525226 0.702069846 0.702613296 0.703155607
## PC637      PC638      PC639      PC640      PC641      PC642
## 0.703696583 0.704236364 0.704775599 0.705313359 0.705850719 0.706387235
## PC643      PC644      PC645      PC646      PC647      PC648
## 0.706923388 0.707458813 0.707993801 0.708527922 0.709061215 0.709594187
## PC649      PC650      PC651      PC652      PC653      PC654
## 0.710125772 0.710656485 0.711186307 0.711715755 0.712243278 0.712770048
## PC655      PC656      PC657      PC658      PC659      PC660
## 0.713296260 0.713822274 0.714347424 0.714871831 0.715395055 0.715917134
## PC661      PC662      PC663      PC664      PC665      PC666
## 0.716438701 0.716958674 0.717478429 0.717997882 0.718516264 0.719033948
## PC667      PC668      PC669      PC670      PC671      PC672
## 0.719550714 0.720066457 0.720581186 0.721095209 0.721608420 0.722121084
## PC673      PC674      PC675      PC676      PC677      PC678
## 0.722633166 0.723143283 0.723652880 0.724161710 0.724670367 0.725177681
## PC679      PC680      PC681      PC682      PC683      PC684
## 0.725684197 0.726190326 0.726696170 0.727201762 0.727706435 0.728210097
## PC685      PC686      PC687      PC688      PC689      PC690
## 0.728713115 0.729215416 0.729716266 0.730216766 0.730716562 0.731215329
## PC691      PC692      PC693      PC694      PC695      PC696
## 0.731713594 0.732211398 0.732708636 0.733205313 0.733700484 0.734195354
## PC697      PC698      PC699      PC700      PC701      PC702
## 0.734689205 0.735181978 0.735674155 0.736165665 0.736656713 0.737146339
## PC703      PC704      PC705      PC706      PC707      PC708
## 0.737635834 0.738124214 0.738612192 0.739099376 0.739586086 0.740072453
## PC709      PC710      PC711      PC712      PC713      PC714
## 0.740557458 0.741041570 0.741525072 0.742008158 0.742490828 0.742972148
## PC715      PC716      PC717      PC718      PC719      PC720
## 0.743452849 0.743932891 0.744412058 0.744890577 0.745368040 0.745844561
## PC721      PC722      PC723      PC724      PC725      PC726

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## 0.746320232 0.746795429 0.747269815 0.747743559 0.748216572 0.748689010
## PC727      PC728      PC729      PC730      PC731      PC732
## 0.749160520 0.749631692 0.750102194 0.750572353 0.751041441 0.751509553
## PC733      PC734      PC735      PC736      PC737      PC738
## 0.751976768 0.752443465 0.752909758 0.753374366 0.753838416 0.754302068
## PC739      PC740      PC741      PC742      PC743      PC744
## 0.754764447 0.755226515 0.755688102 0.756149474 0.756609702 0.757069313
## PC745      PC746      PC747      PC748      PC749      PC750
## 0.757528468 0.757987217 0.758444967 0.758902352 0.759359348 0.759815862
## PC751      PC752      PC753      PC754      PC755      PC756
## 0.760271347 0.760725635 0.761179434 0.761632929 0.762085818 0.762537292
## PC757      PC758      PC759      PC760      PC761      PC762
## 0.762988298 0.763439189 0.763889378 0.764339188 0.764788664 0.765236858
## PC763      PC764      PC765      PC766      PC767      PC768
## 0.765684641 0.766131528 0.766576833 0.767021911 0.767465982 0.767909755
## PC769      PC770      PC771      PC772      PC773      PC774
## 0.768353010 0.768795616 0.769237500 0.769678311 0.770118940 0.770558361
## PC775      PC776      PC777      PC778      PC779      PC780
## 0.770996799 0.771434891 0.771872376 0.772309707 0.772746293 0.773182117
## PC781      PC782      PC783      PC784      PC785      PC786
## 0.773617085 0.774051688 0.774485507 0.774918885 0.775351124 0.775782472
## PC787      PC788      PC789      PC790      PC791      PC792
## 0.776213075 0.776643296 0.777073434 0.777502620 0.777931272 0.778359293
## PC793      PC794      PC795      PC796      PC797      PC798
## 0.778786456 0.779212588 0.779638149 0.780062263 0.780486261 0.780909876
## PC799      PC800      PC801      PC802      PC803      PC804
## 0.781332965 0.781755061 0.782176664 0.782597343 0.783016772 0.783435790
## PC805      PC806      PC807      PC808      PC809      PC810
## 0.783854039 0.784271379 0.784688630 0.785105244 0.785521453 0.785937159
## PC811      PC812      PC813      PC814      PC815      PC816
## 0.786351771 0.786766068 0.787179762 0.787593282 0.788006232 0.788418621
## PC817      PC818      PC819      PC820      PC821      PC822
## 0.788830129 0.789241013 0.789651362 0.790061223 0.790470385 0.790878911
## PC823      PC824      PC825      PC826      PC827      PC828
## 0.791286189 0.791693053 0.792099458 0.792505487 0.792910937 0.793314846
## PC829      PC830      PC831      PC832      PC833      PC834
## 0.793718237 0.794121209 0.794524005 0.794926137 0.795327257 0.795727657
## PC835      PC836      PC837      PC838      PC839      PC840
## 0.796127735 0.796526944 0.796925818 0.797324360 0.797722016 0.798118597
## PC841      PC842      PC843      PC844      PC845      PC846
## 0.798515075 0.798911370 0.799307173 0.799701503 0.800095616 0.800488805
## PC847      PC848      PC849      PC850      PC851      PC852
## 0.800881923 0.801274604 0.801666680 0.802057972 0.802448320 0.802838497
## PC853      PC854      PC855      PC856      PC857      PC858
## 0.803228111 0.803617271 0.804006046 0.804394556 0.804782185 0.805168845
## PC859      PC860      PC861      PC862      PC863      PC864
## 0.805555174 0.805940493 0.806325272 0.806709237 0.807093003 0.807475888
## PC865      PC866      PC867      PC868      PC869      PC870
## 0.807858555 0.808240116 0.808621598 0.809002644 0.809382528 0.809762036
## PC871      PC872      PC873      PC874      PC875      PC876
## 0.810140514 0.810518498 0.810895905 0.811272971 0.811649410 0.812025697
## PC877      PC878      PC879      PC880      PC881      PC882
## 0.812401128 0.812775828 0.813150319 0.813524312 0.813897771 0.814270162
## PC883      PC884      PC885      PC886      PC887      PC888

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## 0.814642117 0.815013576 0.815384315 0.815754747 0.816124386 0.816493442
## PC889      PC890      PC891      PC892      PC893      PC894
## 0.816861526 0.817228973 0.817596210 0.817962865 0.818328774 0.818693786
## PC895      PC896      PC897      PC898      PC899      PC900
## 0.819058345 0.819422436 0.819786109 0.820149553 0.820511979 0.820873859
## PC901      PC902      PC903      PC904      PC905      PC906
## 0.821234789 0.821594956 0.821954860 0.822314476 0.822673530 0.823031935
## PC907      PC908      PC909      PC910      PC911      PC912
## 0.823389767 0.823747218 0.824104046 0.824460029 0.824815632 0.825170742
## PC913      PC914      PC915      PC916      PC917      PC918
## 0.825525381 0.825879688 0.826233255 0.826586655 0.826939398 0.827291763
## PC919      PC920      PC921      PC922      PC923      PC924
## 0.827643466 0.827994744 0.828345221 0.828695340 0.829044407 0.829393310
## PC925      PC926      PC927      PC928      PC929      PC930
## 0.829741725 0.830090123 0.830437736 0.830784731 0.831131359 0.831476879
## PC931      PC932      PC933      PC934      PC935      PC936
## 0.831822372 0.832166804 0.832510911 0.832854803 0.833197824 0.833539449
## PC937      PC938      PC939      PC940      PC941      PC942
## 0.833880939 0.834221669 0.834562192 0.834902204 0.835241686 0.835580519
## PC943      PC944      PC945      PC946      PC947      PC948
## 0.835918468 0.836256178 0.836593357 0.836930286 0.837266579 0.837602186
## PC949      PC950      PC951      PC952      PC953      PC954
## 0.837936720 0.838270986 0.838604793 0.838938508 0.839271259 0.839603475
## PC955      PC956      PC957      PC958      PC959      PC960
## 0.839935062 0.840266230 0.840596800 0.840927022 0.841257006 0.841586040
## PC961      PC962      PC963      PC964      PC965      PC966
## 0.841914817 0.842243105 0.842571182 0.842898447 0.843224748 0.843550106
## PC967      PC968      PC969      PC970      PC971      PC972
## 0.843875152 0.844200010 0.844524245 0.844847871 0.845171196 0.845494390
## PC973      PC974      PC975      PC976      PC977      PC978
## 0.845816807 0.846138710 0.846459422 0.846779811 0.847099910 0.847419758
## PC979      PC980      PC981      PC982      PC983      PC984
## 0.847738620 0.848057418 0.848375948 0.848694077 0.849010882 0.849327657
## PC985      PC986      PC987      PC988      PC989      PC990
## 0.849644083 0.849960066 0.850275262 0.850589752 0.850903779 0.851217634
## PC991      PC992      PC993      PC994      PC995      PC996
## 0.851531211 0.851844372 0.852157103 0.852469210 0.852780945 0.853092231
## PC997      PC998      PC999      PC1000     PC1001     PC1002
## 0.853402836 0.853713011 0.854022370 0.854331414 0.854639790 0.854947938
## PC1003     PC1004     PC1005     PC1006     PC1007     PC1008
## 0.855255506 0.855562889 0.855869585 0.856176151 0.856482469 0.856788172
## PC1009     PC1010     PC1011     PC1012     PC1013     PC1014
## 0.857093362 0.857398365 0.857702973 0.858006886 0.858310244 0.858612972
## PC1015     PC1016     PC1017     PC1018     PC1019     PC1020
## 0.858914806 0.859216332 0.859517509 0.859818435 0.860119008 0.860418556
## PC1021     PC1022     PC1023     PC1024     PC1025     PC1026
## 0.860716982 0.861015309 0.861313115 0.861610600 0.861907699 0.862204632
## PC1027     PC1028     PC1029     PC1030     PC1031     PC1032
## 0.862500699 0.862796476 0.863091740 0.863386517 0.863681122 0.863975194
## PC1033     PC1034     PC1035     PC1036     PC1037     PC1038
## 0.864268826 0.864561924 0.864854555 0.865146377 0.865437861 0.865728906
## PC1039     PC1040     PC1041     PC1042     PC1043     PC1044
## 0.866019572 0.866309652 0.866599467 0.866888534 0.867177099 0.867465498
## PC1045     PC1046     PC1047     PC1048     PC1049     PC1050

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## 0.867753310 0.868040284 0.868326777 0.868612878 0.868898640 0.869184226
## PC1051      PC1052      PC1053      PC1054      PC1055      PC1056
## 0.869469434 0.869753862 0.870037664 0.870321144 0.870604389 0.870887052
## PC1057      PC1058      PC1059      PC1060      PC1061      PC1062
## 0.871169153 0.871450448 0.871731293 0.872011726 0.872291752 0.872571335
## PC1063      PC1064      PC1065      PC1066      PC1067      PC1068
## 0.872850734 0.873129742 0.873408217 0.873686055 0.873963526 0.874240555
## PC1069      PC1070      PC1071      PC1072      PC1073      PC1074
## 0.874516993 0.874793042 0.875068634 0.875343814 0.875618454 0.875892443
## PC1075      PC1076      PC1077      PC1078      PC1079      PC1080
## 0.876166384 0.876439563 0.876712355 0.876985016 0.877257259 0.877529067
## PC1081      PC1082      PC1083      PC1084      PC1085      PC1086
## 0.877800564 0.878071676 0.878341984 0.878611930 0.878881542 0.879150810
## PC1087      PC1088      PC1089      PC1090      PC1091      PC1092
## 0.879419774 0.879687853 0.879955654 0.880223184 0.880489583 0.880755688
## PC1093      PC1094      PC1095      PC1096      PC1097      PC1098
## 0.881021540 0.881286896 0.881551454 0.881815878 0.882079895 0.882343586
## PC1099      PC1100      PC1101      PC1102      PC1103      PC1104
## 0.882607023 0.882870039 0.883132196 0.883394178 0.883655132 0.883915817
## PC1105      PC1106      PC1107      PC1108      PC1109      PC1110
## 0.884176293 0.884436475 0.884695866 0.884955165 0.885214120 0.885472532
## PC1111      PC1112      PC1113      PC1114      PC1115      PC1116
## 0.885730698 0.885988448 0.886245772 0.886502392 0.886758423 0.887013959
## PC1117      PC1118      PC1119      PC1120      PC1121      PC1122
## 0.887269341 0.887524217 0.887778715 0.888033038 0.888287154 0.888540725
## PC1123      PC1124      PC1125      PC1126      PC1127      PC1128
## 0.888793957 0.889046590 0.889299095 0.889550864 0.889802589 0.890053795
## PC1129      PC1130      PC1131      PC1132      PC1133      PC1134
## 0.890304537 0.890554683 0.890804750 0.891054527 0.891303638 0.891552161
## PC1135      PC1136      PC1137      PC1138      PC1139      PC1140
## 0.891800317 0.892048214 0.892295845 0.892542924 0.892789669 0.893035740
## PC1141      PC1142      PC1143      PC1144      PC1145      PC1146
## 0.893281399 0.893526812 0.893772010 0.894016409 0.894260556 0.894504404
## PC1147      PC1148      PC1149      PC1150      PC1151      PC1152
## 0.894747525 0.894990393 0.895232654 0.895474509 0.895716188 0.895957349
## PC1153      PC1154      PC1155      PC1156      PC1157      PC1158
## 0.896198396 0.896438969 0.896678508 0.896917741 0.897156898 0.897395517
## PC1159      PC1160      PC1161      PC1162      PC1163      PC1164
## 0.897633561 0.897871354 0.898108865 0.898346126 0.898582580 0.898818573
## PC1165      PC1166      PC1167      PC1168      PC1169      PC1170
## 0.899054468 0.899290176 0.899525541 0.899760582 0.899994941 0.900229067
## PC1171      PC1172      PC1173      PC1174      PC1175      PC1176
## 0.900462639 0.900695434 0.900928077 0.901160516 0.901392758 0.901624418
## PC1177      PC1178      PC1179      PC1180      PC1181      PC1182
## 0.901855611 0.902086748 0.902317626 0.902547698 0.902777579 0.903007321
## PC1183      PC1184      PC1185      PC1186      PC1187      PC1188
## 0.903236799 0.903465933 0.903694536 0.903922806 0.904150714 0.904377931
## PC1189      PC1190      PC1191      PC1192      PC1193      PC1194
## 0.904604843 0.904831202 0.905057076 0.905282564 0.905507528 0.905732062
## PC1195      PC1196      PC1197      PC1198      PC1199      PC1200
## 0.905955945 0.906179207 0.906402104 0.906624718 0.906847187 0.907069229
## PC1201      PC1202      PC1203      PC1204      PC1205      PC1206
## 0.907290810 0.907512340 0.907732912 0.907953355 0.908173347 0.908393109
## PC1207      PC1208      PC1209      PC1210      PC1211      PC1212

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## 0.908612540 0.908831236 0.909049642 0.909267821 0.909485555 0.909703051
## PC1213 PC1214 PC1215 PC1216 PC1217 PC1218
## 0.909919955 0.910136678 0.910352805 0.910568793 0.910784688 0.911000103
## PC1219 PC1220 PC1221 PC1222 PC1223 PC1224
## 0.911214839 0.911429440 0.911643788 0.911857656 0.912071292 0.912284673
## PC1225 PC1226 PC1227 PC1228 PC1229 PC1230
## 0.912497494 0.912710023 0.912922386 0.913133978 0.913344774 0.913555246
## PC1231 PC1232 PC1233 PC1234 PC1235 PC1236
## 0.913765395 0.913975434 0.914185364 0.914394528 0.914603500 0.914812245
## PC1237 PC1238 PC1239 PC1240 PC1241 PC1242
## 0.915020518 0.915228693 0.915436072 0.915643352 0.915850358 0.916056821
## PC1243 PC1244 PC1245 PC1246 PC1247 PC1248
## 0.916262854 0.916468296 0.916673311 0.916878160 0.917082900 0.917286798
## PC1249 PC1250 PC1251 PC1252 PC1253 PC1254
## 0.917490485 0.917693947 0.917897119 0.918100185 0.918302605 0.918504315
## PC1255 PC1256 PC1257 PC1258 PC1259 PC1260
## 0.918705950 0.918907292 0.919108275 0.919308967 0.919509323 0.919709267
## PC1261 PC1262 PC1263 PC1264 PC1265 PC1266
## 0.919908790 0.920107757 0.920306602 0.920505119 0.920703500 0.920901164
## PC1267 PC1268 PC1269 PC1270 PC1271 PC1272
## 0.921098638 0.921295902 0.921492761 0.921689434 0.921885757 0.922081780
## PC1273 PC1274 PC1275 PC1276 PC1277 PC1278
## 0.922277615 0.922473097 0.922668459 0.922863564 0.923057833 0.923251820
## PC1279 PC1280 PC1281 PC1282 PC1283 PC1284
## 0.923445183 0.923638306 0.923831375 0.924024112 0.924216423 0.924408425
## PC1285 PC1286 PC1287 PC1288 PC1289 PC1290
## 0.924600000 0.924791242 0.924981915 0.925172418 0.925362598 0.925552182
## PC1291 PC1292 PC1293 PC1294 PC1295 PC1296
## 0.925741618 0.925930464 0.926119093 0.926307588 0.926495249 0.926682692
## PC1297 PC1298 PC1299 PC1300 PC1301 PC1302
## 0.926870002 0.927057242 0.927243893 0.927430042 0.927616032 0.927801567
## PC1303 PC1304 PC1305 PC1306 PC1307 PC1308
## 0.927986713 0.928171703 0.928356494 0.928541003 0.928724668 0.928908228
## PC1309 PC1310 PC1311 PC1312 PC1313 PC1314
## 0.929091437 0.929274207 0.929456771 0.929638897 0.929820787 0.930002048
## PC1315 PC1316 PC1317 PC1318 PC1319 PC1320
## 0.930182994 0.930363669 0.930543844 0.930723916 0.930903465 0.931082881
## PC1321 PC1322 PC1323 PC1324 PC1325 PC1326
## 0.931262080 0.931441179 0.931619752 0.931797834 0.931975900 0.932153648
## PC1327 PC1328 PC1329 PC1330 PC1331 PC1332
## 0.932330858 0.932507672 0.932684119 0.932860153 0.933036012 0.933211465
## PC1333 PC1334 PC1335 PC1336 PC1337 PC1338
## 0.933386444 0.933561104 0.933735582 0.933909638 0.934083167 0.934256458
## PC1339 PC1340 PC1341 PC1342 PC1343 PC1344
## 0.934429387 0.934602272 0.934774703 0.934947060 0.935118810 0.935290495
## PC1345 PC1346 PC1347 PC1348 PC1349 PC1350
## 0.935461786 0.935633018 0.935803814 0.935974362 0.936144493 0.936314280
## PC1351 PC1352 PC1353 PC1354 PC1355 PC1356
## 0.936483585 0.936652656 0.936821697 0.936990195 0.937158225 0.937325755
## PC1357 PC1358 PC1359 PC1360 PC1361 PC1362
## 0.937492967 0.937659892 0.937826766 0.937993297 0.938159686 0.938325711
## PC1363 PC1364 PC1365 PC1366 PC1367 PC1368
## 0.938491225 0.938656553 0.938821501 0.938986204 0.939150573 0.939314633
## PC1369 PC1370 PC1371 PC1372 PC1373 PC1374

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## 0.939478404 0.939641819 0.939805201 0.939967876 0.940130253 0.940292446
## PC1375 PC1376 PC1377 PC1378 PC1379 PC1380
## 0.940454564 0.940615989 0.940776957 0.940937563 0.941097729 0.941257870
## PC1381 PC1382 PC1383 PC1384 PC1385 PC1386
## 0.941417843 0.941577535 0.941736785 0.941895756 0.942054562 0.942213136
## PC1387 PC1388 PC1389 PC1390 PC1391 PC1392
## 0.942371412 0.942529165 0.942686734 0.942843991 0.943000888 0.943157599
## PC1393 PC1394 PC1395 PC1396 PC1397 PC1398
## 0.943314021 0.943470224 0.943625823 0.943781162 0.943935916 0.944090354
## PC1399 PC1400 PC1401 PC1402 PC1403 PC1404
## 0.944244599 0.944398722 0.944552359 0.944705801 0.944858868 0.945011845
## PC1405 PC1406 PC1407 PC1408 PC1409 PC1410
## 0.945164588 0.945317169 0.945469371 0.945621289 0.945772732 0.945923836
## PC1411 PC1412 PC1413 PC1414 PC1415 PC1416
## 0.946074362 0.946224737 0.946374931 0.946524912 0.946674465 0.946823806
## PC1417 PC1418 PC1419 PC1420 PC1421 PC1422
## 0.946972829 0.947121475 0.947269809 0.947417939 0.947565728 0.947713239
## PC1423 PC1424 PC1425 PC1426 PC1427 PC1428
## 0.947860571 0.948007696 0.948154502 0.948300899 0.948447213 0.948593095
## PC1429 PC1430 PC1431 PC1432 PC1433 PC1434
## 0.948738824 0.948884040 0.949029087 0.949174071 0.949318663 0.949462880
## PC1435 PC1436 PC1437 PC1438 PC1439 PC1440
## 0.949607045 0.949750761 0.949894058 0.950037103 0.950180000 0.950322660
## PC1441 PC1442 PC1443 PC1444 PC1445 PC1446
## 0.950465240 0.950607331 0.950749328 0.950891045 0.951032224 0.951173316
## PC1447 PC1448 PC1449 PC1450 PC1451 PC1452
## 0.951313805 0.951454103 0.951594063 0.951733712 0.951873014 0.952012134
## PC1453 PC1454 PC1455 PC1456 PC1457 PC1458
## 0.952150742 0.952288994 0.952427189 0.952564987 0.952702442 0.952839524
## PC1459 PC1460 PC1461 PC1462 PC1463 PC1464
## 0.952976154 0.953112554 0.953248830 0.953384986 0.953520723 0.953656302
## PC1465 PC1466 PC1467 PC1468 PC1469 PC1470
## 0.953791690 0.953926718 0.954061535 0.954196144 0.954330563 0.954464655
## PC1471 PC1472 PC1473 PC1474 PC1475 PC1476
## 0.954598415 0.954732067 0.954865411 0.954998640 0.955131305 0.955263722
## PC1477 PC1478 PC1479 PC1480 PC1481 PC1482
## 0.955395736 0.955527339 0.955658616 0.955789644 0.955920526 0.956051315
## PC1483 PC1484 PC1485 PC1486 PC1487 PC1488
## 0.956181468 0.956311544 0.956441406 0.956570908 0.956700209 0.956829384
## PC1489 PC1490 PC1491 PC1492 PC1493 PC1494
## 0.956958224 0.957086876 0.957215462 0.957343521 0.957471297 0.957598798
## PC1495 PC1496 PC1497 PC1498 PC1499 PC1500
## 0.957726060 0.957853054 0.957979860 0.958106480 0.958232672 0.958358587
## PC1501 PC1502 PC1503 PC1504 PC1505 PC1506
## 0.958484227 0.958609587 0.958734650 0.958859555 0.958984254 0.959108654
## PC1507 PC1508 PC1509 PC1510 PC1511 PC1512
## 0.959232832 0.959356819 0.959480542 0.959604091 0.959727428 0.959850381
## PC1513 PC1514 PC1515 PC1516 PC1517 PC1518
## 0.959973127 0.960095670 0.960217681 0.960339295 0.960460688 0.960581821
## PC1519 PC1520 PC1521 PC1522 PC1523 PC1524
## 0.960702829 0.960823785 0.960944512 0.961065030 0.961184989 0.961304814
## PC1525 PC1526 PC1527 PC1528 PC1529 PC1530
## 0.961424309 0.961543520 0.961662521 0.961781298 0.961899784 0.962018190
## PC1531 PC1532 PC1533 PC1534 PC1535 PC1536

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## 0.962136199 0.962253960 0.962371461 0.962488751 0.962605937 0.962722633
## PC1537 PC1538 PC1539 PC1540 PC1541 PC1542
## 0.962839134 0.962955275 0.963071169 0.963186767 0.963301891 0.963416819
## PC1543 PC1544 PC1545 PC1546 PC1547 PC1548
## 0.963531640 0.963646316 0.963760772 0.963875164 0.963989071 0.964102920
## PC1549 PC1550 PC1551 PC1552 PC1553 PC1554
## 0.964216550 0.964329930 0.964442980 0.964555938 0.964668551 0.964780909
## PC1555 PC1556 PC1557 PC1558 PC1559 PC1560
## 0.964893045 0.965004990 0.965116760 0.965228195 0.965339302 0.965450233
## PC1561 PC1562 PC1563 PC1564 PC1565 PC1566
## 0.965561028 0.965671686 0.965782089 0.965892393 0.966002562 0.966112377
## PC1567 PC1568 PC1569 PC1570 PC1571 PC1572
## 0.966221921 0.966331117 0.966439967 0.966548675 0.966657042 0.966765257
## PC1573 PC1574 PC1575 PC1576 PC1577 PC1578
## 0.966873117 0.966980753 0.967088234 0.967195557 0.967302436 0.967409196
## PC1579 PC1580 PC1581 PC1582 PC1583 PC1584
## 0.967515803 0.967622127 0.967728324 0.967834224 0.967939811 0.968045153
## PC1585 PC1586 PC1587 PC1588 PC1589 PC1590
## 0.968150273 0.968255115 0.968359618 0.968464077 0.968568185 0.968672242
## PC1591 PC1592 PC1593 PC1594 PC1595 PC1596
## 0.968775906 0.968879514 0.968982916 0.969085936 0.969188898 0.969291529
## PC1597 PC1598 PC1599 PC1600 PC1601 PC1602
## 0.969393916 0.969496120 0.969597938 0.969699730 0.969801177 0.969902353
## PC1603 PC1604 PC1605 PC1606 PC1607 PC1608
## 0.970003401 0.970104201 0.970204761 0.970305020 0.970405114 0.970504837
## PC1609 PC1610 PC1611 PC1612 PC1613 PC1614
## 0.970604433 0.970703694 0.970802701 0.970901557 0.971000266 0.971098603
## PC1615 PC1616 PC1617 PC1618 PC1619 PC1620
## 0.971196488 0.971294272 0.971391937 0.971489153 0.971586124 0.971683022
## PC1621 PC1622 PC1623 PC1624 PC1625 PC1626
## 0.971779830 0.971876228 0.971972415 0.972068522 0.972164402 0.972260070
## PC1627 PC1628 PC1629 PC1630 PC1631 PC1632
## 0.972355498 0.972450733 0.972545845 0.972640711 0.972735367 0.972829710
## PC1633 PC1634 PC1635 PC1636 PC1637 PC1638
## 0.972923970 0.973017739 0.973111386 0.973204775 0.973297864 0.973390916
## PC1639 PC1640 PC1641 PC1642 PC1643 PC1644
## 0.973483852 0.973576349 0.973668824 0.973760655 0.973852325 0.973943826
## PC1645 PC1646 PC1647 PC1648 PC1649 PC1650
## 0.974035266 0.974126386 0.974217416 0.974308315 0.974398963 0.974489265
## PC1651 PC1652 PC1653 PC1654 PC1655 PC1656
## 0.974579397 0.974669448 0.974759294 0.974848943 0.974938205 0.975027267
## PC1657 PC1658 PC1659 PC1660 PC1661 PC1662
## 0.975116203 0.975204872 0.975293442 0.975381811 0.975469832 0.975557572
## PC1663 PC1664 PC1665 PC1666 PC1667 PC1668
## 0.975645073 0.975732475 0.975819667 0.975906836 0.975993570 0.976080235
## PC1669 PC1670 PC1671 PC1672 PC1673 PC1674
## 0.976166689 0.976252999 0.976338944 0.976424539 0.976510074 0.976595337
## PC1675 PC1676 PC1677 PC1678 PC1679 PC1680
## 0.976680424 0.976765257 0.976849872 0.976934390 0.977018564 0.977102491
## PC1681 PC1682 PC1683 PC1684 PC1685 PC1686
## 0.977186278 0.977270027 0.977353291 0.977436408 0.977519406 0.977602172
## PC1687 PC1688 PC1689 PC1690 PC1691 PC1692
## 0.977684745 0.977767281 0.977849701 0.977931642 0.978013424 0.978094929
## PC1693 PC1694 PC1695 PC1696 PC1697 PC1698

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## 0.978176402 0.978257551 0.978338622 0.978419465 0.978499951 0.978580299
## PC1699 PC1700 PC1701 PC1702 PC1703 PC1704
## 0.978660561 0.978740722 0.978820680 0.978900323 0.978979612 0.979058718
## PC1705 PC1706 PC1707 PC1708 PC1709 PC1710
## 0.979137757 0.979216581 0.979295335 0.979373712 0.979451815 0.979529838
## PC1711 PC1712 PC1713 PC1714 PC1715 PC1716
## 0.979607681 0.979685404 0.979762952 0.979840421 0.979917698 0.979994711
## PC1717 PC1718 PC1719 PC1720 PC1721 PC1722
## 0.980071624 0.980148444 0.980224960 0.980301282 0.980377342 0.980453179
## PC1723 PC1724 PC1725 PC1726 PC1727 PC1728
## 0.980528789 0.980604149 0.980679266 0.980754199 0.980829007 0.980903512
## PC1729 PC1730 PC1731 PC1732 PC1733 PC1734
## 0.980977948 0.981051959 0.981125882 0.981199593 0.981273151 0.981346613
## PC1735 PC1736 PC1737 PC1738 PC1739 PC1740
## 0.981419893 0.981493034 0.981566094 0.981639019 0.981711524 0.981783853
## PC1741 PC1742 PC1743 PC1744 PC1745 PC1746
## 0.981856136 0.981928057 0.981999794 0.982071343 0.982142551 0.982213724
## PC1747 PC1748 PC1749 PC1750 PC1751 PC1752
## 0.982284790 0.982355413 0.982425859 0.982496218 0.982566352 0.982636163
## PC1753 PC1754 PC1755 PC1756 PC1757 PC1758
## 0.982705874 0.982775515 0.982845054 0.982914267 0.982983349 0.983052385
## PC1759 PC1760 PC1761 PC1762 PC1763 PC1764
## 0.983121299 0.983189870 0.983258377 0.983326667 0.983394726 0.983462671
## PC1765 PC1766 PC1767 PC1768 PC1769 PC1770
## 0.983530372 0.983597961 0.983665345 0.983732544 0.983799554 0.983866525
## PC1771 PC1772 PC1773 PC1774 PC1775 PC1776
## 0.983933237 0.983999787 0.984065956 0.984132053 0.984197941 0.984263749
## PC1777 PC1778 PC1779 PC1780 PC1781 PC1782
## 0.984329295 0.984394553 0.984459734 0.984524741 0.984589505 0.984654084
## PC1783 PC1784 PC1785 PC1786 PC1787 PC1788
## 0.984718399 0.984782492 0.984846510 0.984910273 0.984973961 0.985037468
## PC1789 PC1790 PC1791 PC1792 PC1793 PC1794
## 0.985100768 0.985163927 0.985226887 0.985289767 0.985352281 0.985414516
## PC1795 PC1796 PC1797 PC1798 PC1799 PC1800
## 0.985476533 0.985538493 0.985600162 0.985661773 0.985723097 0.985784333
## PC1801 PC1802 PC1803 PC1804 PC1805 PC1806
## 0.985845442 0.985906438 0.985967266 0.986027882 0.986088241 0.986148511
## PC1807 PC1808 PC1809 PC1810 PC1811 PC1812
## 0.986208630 0.986268582 0.986328153 0.986387667 0.986447150 0.986506386
## PC1813 PC1814 PC1815 PC1816 PC1817 PC1818
## 0.986565488 0.986624466 0.986683305 0.986742048 0.986800601 0.986858972
## PC1819 PC1820 PC1821 PC1822 PC1823 PC1824
## 0.986917111 0.986975138 0.987032894 0.987090547 0.987148008 0.987205271
## PC1825 PC1826 PC1827 PC1828 PC1829 PC1830
## 0.987262454 0.987319585 0.987376608 0.987433443 0.987489931 0.987546241
## PC1831 PC1832 PC1833 PC1834 PC1835 PC1836
## 0.987602446 0.987658419 0.987714316 0.987769884 0.987825329 0.987880576
## PC1837 PC1838 PC1839 PC1840 PC1841 PC1842
## 0.987935588 0.987990391 0.988045098 0.988099657 0.988154058 0.988208319
## PC1843 PC1844 PC1845 PC1846 PC1847 PC1848
## 0.988262396 0.988316365 0.988370130 0.988423770 0.988477212 0.988530498
## PC1849 PC1850 PC1851 PC1852 PC1853 PC1854
## 0.988583552 0.988636538 0.988689414 0.988742041 0.988794549 0.988846928
## PC1855 PC1856 PC1857 PC1858 PC1859 PC1860

```

```

## 0.988899101 0.988951158 0.989003146 0.989054918 0.989106410 0.989157766
## PC1861      PC1862      PC1863      PC1864      PC1865      PC1866
## 0.989209005 0.989260131 0.989311059 0.989361900 0.989412695 0.989463320
## PC1867      PC1868      PC1869      PC1870      PC1871      PC1872
## 0.989513755 0.989564047 0.989614062 0.989664031 0.989713960 0.989763759
## PC1873      PC1874      PC1875      PC1876      PC1877      PC1878
## 0.989813307 0.989862800 0.989912130 0.989961352 0.990010359 0.990059317
## PC1879      PC1880      PC1881      PC1882      PC1883      PC1884
## 0.990108076 0.990156694 0.990205150 0.990253382 0.990301483 0.990349358
## PC1885      PC1886      PC1887      PC1888      PC1889      PC1890
## 0.990397087 0.990444667 0.990492123 0.990539270 0.990586357 0.990633146
## PC1891      PC1892      PC1893      PC1894      PC1895      PC1896
## 0.990679831 0.990726400 0.990772865 0.990819248 0.990865405 0.990911472
## PC1897      PC1898      PC1899      PC1900      PC1901      PC1902
## 0.990957340 0.991002982 0.991048470 0.991093850 0.991139115 0.991184277
## PC1903      PC1904      PC1905      PC1906      PC1907      PC1908
## 0.991229283 0.991274099 0.991318694 0.991363185 0.991407582 0.991451908
## PC1909      PC1910      PC1911      PC1912      PC1913      PC1914
## 0.991496110 0.991540027 0.991583756 0.991627299 0.991670810 0.991714171
## PC1915      PC1916      PC1917      PC1918      PC1919      PC1920
## 0.991757488 0.991800538 0.991843509 0.991886248 0.991928923 0.991971391
## PC1921      PC1922      PC1923      PC1924      PC1925      PC1926
## 0.992013709 0.992055872 0.992097792 0.992139452 0.992181034 0.992222557
## PC1927      PC1928      PC1929      PC1930      PC1931      PC1932
## 0.992263983 0.992305176 0.992346272 0.992387188 0.992428044 0.992468699
## PC1933      PC1934      PC1935      PC1936      PC1937      PC1938
## 0.992509287 0.992549639 0.992589937 0.992630066 0.992670134 0.992709977
## PC1939      PC1940      PC1941      PC1942      PC1943      PC1944
## 0.992749717 0.992789396 0.992828912 0.992868348 0.992907686 0.992946786
## PC1945      PC1946      PC1947      PC1948      PC1949      PC1950
## 0.992985824 0.993024684 0.993063444 0.993102074 0.993140481 0.993178829
## PC1951      PC1952      PC1953      PC1954      PC1955      PC1956
## 0.993216792 0.993254700 0.993292502 0.993330132 0.993367621 0.993404958
## PC1957      PC1958      PC1959      PC1960      PC1961      PC1962
## 0.993442241 0.993479378 0.993516422 0.993553396 0.993590156 0.993626711
## PC1963      PC1964      PC1965      PC1966      PC1967      PC1968
## 0.993663086 0.993699362 0.993735505 0.993771596 0.993807630 0.993843471
## PC1969      PC1970      PC1971      PC1972      PC1973      PC1974
## 0.993879192 0.993914746 0.993950227 0.993985554 0.994020813 0.994055991
## PC1975      PC1976      PC1977      PC1978      PC1979      PC1980
## 0.994090971 0.994125849 0.994160558 0.994195128 0.994229564 0.994263880
## PC1981      PC1982      PC1983      PC1984      PC1985      PC1986
## 0.994298123 0.994332166 0.994366153 0.994399952 0.994433547 0.994466983
## PC1987      PC1988      PC1989      PC1990      PC1991      PC1992
## 0.994500336 0.994533669 0.994566890 0.994599982 0.994632979 0.994665815
## PC1993      PC1994      PC1995      PC1996      PC1997      PC1998
## 0.994698513 0.994731091 0.994763598 0.994795958 0.994828044 0.994860055
## PC1999      PC2000      PC2001      PC2002      PC2003      PC2004
## 0.994891939 0.994923657 0.994955244 0.994986749 0.995018109 0.995049382
## PC2005      PC2006      PC2007      PC2008      PC2009      PC2010
## 0.995080621 0.995111496 0.995142275 0.995172974 0.995203531 0.995234028
## PC2011      PC2012      PC2013      PC2014      PC2015      PC2016
## 0.995264381 0.995294649 0.995324838 0.995354991 0.995384992 0.995414782
## PC2017      PC2018      PC2019      PC2020      PC2021      PC2022

```

```

## 0.995444557 0.995474184 0.995503735 0.995533067 0.995562352 0.995591495
## PC2023 PC2024 PC2025 PC2026 PC2027 PC2028
## 0.995620348 0.995649162 0.995677841 0.995706490 0.995735098 0.995763658
## PC2029 PC2030 PC2031 PC2032 PC2033 PC2034
## 0.995791971 0.995820088 0.995848107 0.995876036 0.995903829 0.995931574
## PC2035 PC2036 PC2037 PC2038 PC2039 PC2040
## 0.995959300 0.995986667 0.996013969 0.996041182 0.996068359 0.996095368
## PC2041 PC2042 PC2043 PC2044 PC2045 PC2046
## 0.996122298 0.996149056 0.996175668 0.996202178 0.996228639 0.996254961
## PC2047 PC2048 PC2049 PC2050 PC2051 PC2052
## 0.996281097 0.996307145 0.996333125 0.996359050 0.996384681 0.996410048
## PC2053 PC2054 PC2055 PC2056 PC2057 PC2058
## 0.996435389 0.996460673 0.996485832 0.996510855 0.996535837 0.996560725
## PC2059 PC2060 PC2061 PC2062 PC2063 PC2064
## 0.996585493 0.996610088 0.996634607 0.996658919 0.996683136 0.996707242
## PC2065 PC2066 PC2067 PC2068 PC2069 PC2070
## 0.996731341 0.996755367 0.996779255 0.996802925 0.996826526 0.996850015
## PC2071 PC2072 PC2073 PC2074 PC2075 PC2076
## 0.996873435 0.996896730 0.996919873 0.996942975 0.996965897 0.996988657
## PC2077 PC2078 PC2079 PC2080 PC2081 PC2082
## 0.997011402 0.997033958 0.997056472 0.997078892 0.997101240 0.997123413
## PC2083 PC2084 PC2085 PC2086 PC2087 PC2088
## 0.997145478 0.997167405 0.997189184 0.997210858 0.997232458 0.997254033
## PC2089 PC2090 PC2091 PC2092 PC2093 PC2094
## 0.997275477 0.997296797 0.997318046 0.997339112 0.997360109 0.997380978
## PC2095 PC2096 PC2097 PC2098 PC2099 PC2100
## 0.997401754 0.997422412 0.997443039 0.997463609 0.997484107 0.997504434
## PC2101 PC2102 PC2103 PC2104 PC2105 PC2106
## 0.997524650 0.997544781 0.997564800 0.997584709 0.997604492 0.997624130
## PC2107 PC2108 PC2109 PC2110 PC2111 PC2112
## 0.997643704 0.997663182 0.997682559 0.997701852 0.997721042 0.997740117
## PC2113 PC2114 PC2115 PC2116 PC2117 PC2118
## 0.997759144 0.997778039 0.997796851 0.997815573 0.997834113 0.997852623
## PC2119 PC2120 PC2121 PC2122 PC2123 PC2124
## 0.997871012 0.997889370 0.997907544 0.997925611 0.997943607 0.997961526
## PC2125 PC2126 PC2127 PC2128 PC2129 PC2130
## 0.997979360 0.997997080 0.998014715 0.998032300 0.998049841 0.998067173
## PC2131 PC2132 PC2133 PC2134 PC2135 PC2136
## 0.998084322 0.998101431 0.998118420 0.998135324 0.998152165 0.998168951
## PC2137 PC2138 PC2139 PC2140 PC2141 PC2142
## 0.998185644 0.998202200 0.998218602 0.998234918 0.998251211 0.998267387
## PC2143 PC2144 PC2145 PC2146 PC2147 PC2148
## 0.998283429 0.998299445 0.998315337 0.998331197 0.998346903 0.998362543
## PC2149 PC2150 PC2151 PC2152 PC2153 PC2154
## 0.998378133 0.998393590 0.998408989 0.998424314 0.998439439 0.998454536
## PC2155 PC2156 PC2157 PC2158 PC2159 PC2160
## 0.998469435 0.998484273 0.998499086 0.998513818 0.998528491 0.998543004
## PC2161 PC2162 PC2163 PC2164 PC2165 PC2166
## 0.998557401 0.998571744 0.998585961 0.998600090 0.998614194 0.998628230
## PC2167 PC2168 PC2169 PC2170 PC2171 PC2172
## 0.998642197 0.998656003 0.998669692 0.998683273 0.998696822 0.998710271
## PC2173 PC2174 PC2175 PC2176 PC2177 PC2178
## 0.998723440 0.998736548 0.998749631 0.998762618 0.998775516 0.998788324
## PC2179 PC2180 PC2181 PC2182 PC2183 PC2184

```

```

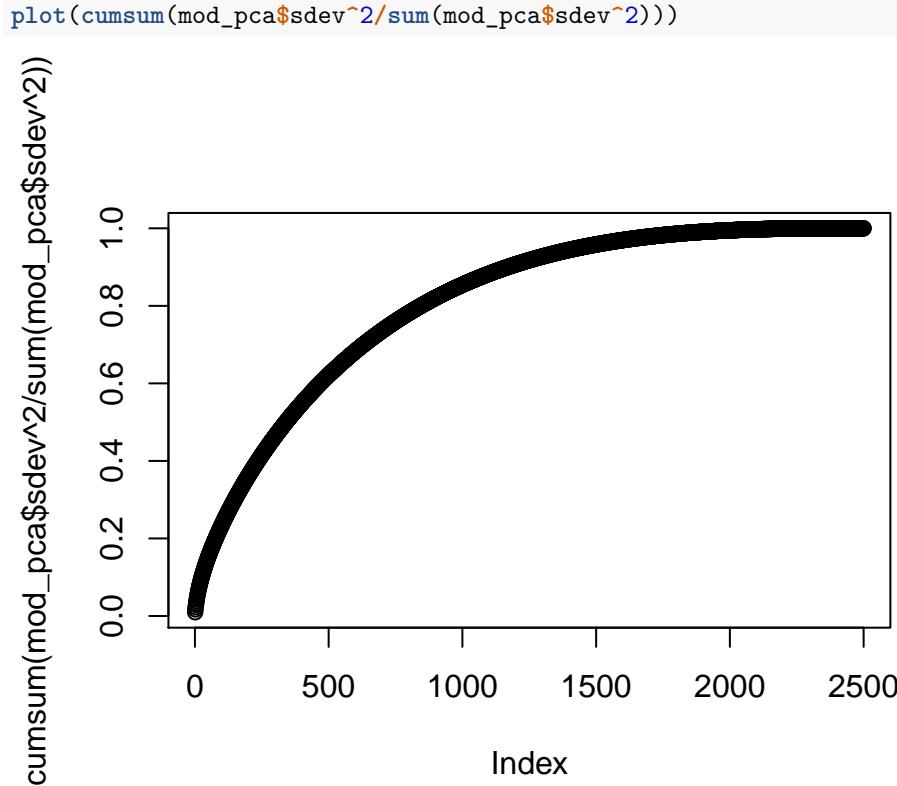
## 0.998801054 0.998813750 0.998826344 0.998838782 0.998851198 0.998863533
## PC2185      PC2186      PC2187      PC2188      PC2189      PC2190
## 0.998875787 0.998887999 0.998900117 0.998912203 0.998924048 0.998935842
## PC2191      PC2192      PC2193      PC2194      PC2195      PC2196
## 0.998947546 0.998959224 0.998970735 0.998982174 0.998993593 0.999004878
## PC2197      PC2198      PC2199      PC2200      PC2201      PC2202
## 0.999016133 0.999027286 0.999038342 0.999049323 0.999060234 0.999071128
## PC2203      PC2204      PC2205      PC2206      PC2207      PC2208
## 0.999081846 0.999092476 0.999103060 0.999113539 0.999123935 0.999134263
## PC2209      PC2210      PC2211      PC2212      PC2213      PC2214
## 0.999144546 0.999154794 0.999164914 0.999174879 0.999184758 0.999194619
## PC2215      PC2216      PC2217      PC2218      PC2219      PC2220
## 0.999204393 0.999214085 0.999223766 0.999233341 0.999242853 0.999252301
## PC2221      PC2222      PC2223      PC2224      PC2225      PC2226
## 0.999261664 0.999270884 0.999280039 0.999289125 0.999298118 0.999307062
## PC2227      PC2228      PC2229      PC2230      PC2231      PC2232
## 0.999315955 0.999324779 0.999333498 0.999342120 0.999350604 0.999359068
## PC2233      PC2234      PC2235      PC2236      PC2237      PC2238
## 0.999367440 0.999375734 0.999383977 0.999392122 0.999400197 0.999408262
## PC2239      PC2240      PC2241      PC2242      PC2243      PC2244
## 0.999416255 0.999424121 0.999431925 0.999439702 0.999447399 0.999455047
## PC2245      PC2246      PC2247      PC2248      PC2249      PC2250
## 0.999462620 0.999470137 0.999477581 0.999484945 0.999492278 0.999499507
## PC2251      PC2252      PC2253      PC2254      PC2255      PC2256
## 0.999506666 0.999513774 0.999520798 0.999527740 0.999534591 0.999541392
## PC2257      PC2258      PC2259      PC2260      PC2261      PC2262
## 0.999548082 0.999554714 0.999561264 0.999567750 0.999574190 0.999580585
## PC2263      PC2264      PC2265      PC2266      PC2267      PC2268
## 0.999586949 0.999593210 0.999599420 0.999605579 0.999611651 0.999617685
## PC2269      PC2270      PC2271      PC2272      PC2273      PC2274
## 0.999623701 0.999629629 0.999635446 0.999641228 0.999646935 0.999652585
## PC2275      PC2276      PC2277      PC2278      PC2279      PC2280
## 0.999658155 0.999663657 0.999669118 0.999674560 0.999679982 0.999685291
## PC2281      PC2282      PC2283      PC2284      PC2285      PC2286
## 0.999690458 0.999695557 0.999700612 0.999705649 0.999710602 0.999715535
## PC2287      PC2288      PC2289      PC2290      PC2291      PC2292
## 0.999720334 0.999725120 0.999729839 0.999734521 0.999739120 0.999743648
## PC2293      PC2294      PC2295      PC2296      PC2297      PC2298
## 0.999748164 0.999752600 0.999756969 0.999761319 0.999765590 0.999769786
## PC2299      PC2300      PC2301      PC2302      PC2303      PC2304
## 0.999773940 0.999778018 0.999782059 0.999786055 0.999790036 0.999793929
## PC2305      PC2306      PC2307      PC2308      PC2309      PC2310
## 0.999797803 0.999801581 0.999805341 0.999809079 0.999812767 0.999816381
## PC2311      PC2312      PC2313      PC2314      PC2315      PC2316
## 0.999819939 0.999823436 0.999826882 0.999830280 0.999833641 0.999836939
## PC2317      PC2318      PC2319      PC2320      PC2321      PC2322
## 0.999840198 0.999843435 0.999846620 0.999849764 0.999852849 0.999855891
## PC2323      PC2324      PC2325      PC2326      PC2327      PC2328
## 0.999858875 0.999861803 0.999864702 0.999867526 0.999870329 0.999873060
## PC2329      PC2330      PC2331      PC2332      PC2333      PC2334
## 0.999875768 0.999878467 0.999881116 0.999883704 0.999886261 0.999888774
## PC2335      PC2336      PC2337      PC2338      PC2339      PC2340
## 0.999891266 0.999893703 0.999896109 0.999898484 0.999900794 0.999903094
## PC2341      PC2342      PC2343      PC2344      PC2345      PC2346

```

```

## 0.999905339 0.999907545 0.999909712 0.999911835 0.999913909 0.999915967
## PC2347 PC2348 PC2349 PC2350 PC2351 PC2352
## 0.999917994 0.999920011 0.999921997 0.999923956 0.999925864 0.999927755
## PC2353 PC2354 PC2355 PC2356 PC2357 PC2358
## 0.999929607 0.999931426 0.999933191 0.999934928 0.999936657 0.999938332
## PC2359 PC2360 PC2361 PC2362 PC2363 PC2364
## 0.999939989 0.999941626 0.999943229 0.999944797 0.999946352 0.999947872
## PC2365 PC2366 PC2367 PC2368 PC2369 PC2370
## 0.999949360 0.999950806 0.999952243 0.999953653 0.999955037 0.999956391
## PC2371 PC2372 PC2373 PC2374 PC2375 PC2376
## 0.999957709 0.999959022 0.999960321 0.999961608 0.999962863 0.999964103
## PC2377 PC2378 PC2379 PC2380 PC2381 PC2382
## 0.999965317 0.999966503 0.999967658 0.999968812 0.999969923 0.999971017
## PC2383 PC2384 PC2385 PC2386 PC2387 PC2388
## 0.999972109 0.999973166 0.999974199 0.999975184 0.999976162 0.999977116
## PC2389 PC2390 PC2391 PC2392 PC2393 PC2394
## 0.999978031 0.999978915 0.999979785 0.999980623 0.999981448 0.999982259
## PC2395 PC2396 PC2397 PC2398 PC2399 PC2400
## 0.999983060 0.999983836 0.999984587 0.999985311 0.999986008 0.999986690
## PC2401 PC2402 PC2403 PC2404 PC2405 PC2406
## 0.999987346 0.999987975 0.999988589 0.999989193 0.999989760 0.999990312
## PC2407 PC2408 PC2409 PC2410 PC2411 PC2412
## 0.999990858 0.999991388 0.999991905 0.999992416 0.999992913 0.999993385
## PC2413 PC2414 PC2415 PC2416 PC2417 PC2418
## 0.999993828 0.999994267 0.999994695 0.999995108 0.999995508 0.999995888
## PC2419 PC2420 PC2421 PC2422 PC2423 PC2424
## 0.999996231 0.999996540 0.999996830 0.999997113 0.999997382 0.999997626
## PC2425 PC2426 PC2427 PC2428 PC2429 PC2430
## 0.999997858 0.999998079 0.999998278 0.999998474 0.999998654 0.999998827
## PC2431 PC2432 PC2433 PC2434 PC2435 PC2436
## 0.999998951 0.999999071 0.999999177 0.999999281 0.999999375 0.999999465
## PC2437 PC2438 PC2439 PC2440 PC2441 PC2442
## 0.999999549 0.999999624 0.999999696 0.999999755 0.999999805 0.999999846
## PC2443 PC2444 PC2445 PC2446 PC2447 PC2448
## 0.999999877 0.999999905 0.999999930 0.999999952 0.999999967 0.999999977
## PC2449 PC2450 PC2451 PC2452 PC2453 PC2454
## 0.999999986 0.999999995 0.999999999 1.000000000 1.000000000 1.000000000
## PC2455 PC2456 PC2457 PC2458 PC2459 PC2460
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2461 PC2462 PC2463 PC2464 PC2465 PC2466
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2467 PC2468 PC2469 PC2470 PC2471 PC2472
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2473 PC2474 PC2475 PC2476 PC2477 PC2478
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2479 PC2480 PC2481 PC2482 PC2483 PC2484
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2485 PC2486 PC2487 PC2488 PC2489 PC2490
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2491 PC2492 PC2493 PC2494 PC2495 PC2496
## 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000 1.000000000
## PC2497 PC2498 PC2499 PC2500
## 1.000000000 1.000000000 1.000000000 1.000000000

```



## Step 4:

Now that we have run the principal component analysis, we need to wrangle the data so that we can fit some proper classification models.

```
train_class = data.frame(mod_pca$x[,1:730])
train_class['author']=labels
train_load = mod_pca$rotation[,1:730]
test_class_pre <- scale(DTM_test1) %*% train_load
test_class <- as.data.frame(test_class_pre)
test_class['author']=labels1
```

## Step 5:

Now that we have classification-ready training and test sets, and a sufficient principal component analysis that seeks to explain a large portion of the data, we can fit a tree model, specifically aggregating tree models using random forests. This way we can seek to reduce out of sample error as much as possible.

we then seek to test the predictive power of our random forest model. We see that

```
set.seed(1)
rf_model<-randomForest(as.factor(author)~.,data=train_class, mtry=6,importance=TRUE)

rf_predict<-predict(rf_model,data=test_class)
rf_table<-as.data.frame(table(rf_predict,as.factor(test_class$author)))

predicted<-rf_predict
```

```

actual<-as.factor(test_class$author)

temp<-as.data.frame(cbind(actual,predicted))
temp$flag<-ifelse(temp$actual==temp$predicted,1,0)
sum(temp$flag)

## [1] 1881
sum(temp$flag)*100/nrow(temp)

## [1] 75.24

```

## Step 6:

Now that we have a random forest model, we need to run a second model. We chose to run a KNN classification, in large part because of the flexibility of a KNN model. We need to ensure that we don't overfit when choosing a K, but we were interested to see how the improved flexibility over a tree model might improve our out of sample error.

```

train.X = subset(train_class, select = -c(author))
test.X = subset(test_class,select=-c(author))
train.author=as.factor(train_class$author)
test.author=as.factor(test_class$author)

set.seed(1)
knn_pred=knn(train.X,test.X,train.author,k=5)

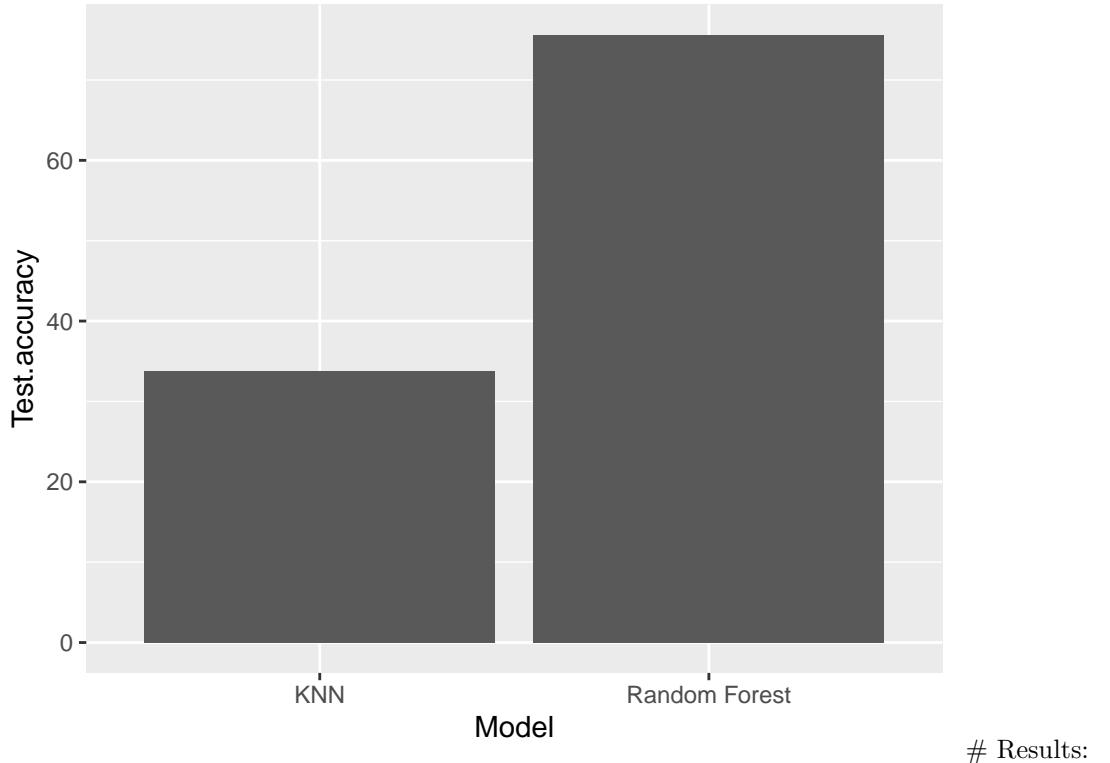
temp_knn=as.data.frame(cbind(knn_pred,test.author))
temp_knn_flag<-ifelse(as.integer(knn_pred)==as.integer(test.author),1,0)
sum(temp_knn_flag)

## [1] 828
sum(temp_knn_flag)*100/nrow(temp_knn)

## [1] 33.12
comp<-data.frame("Model"=c("Random Forest","KNN"), "Test.accuracy"=c(75.6,33.84))
comp

##          Model Test.accuracy
## 1 Random Forest      75.60
## 2          KNN      33.84
ggplot(comp,aes(x=Model,y=Test.accuracy))+geom_col()

```



Clearly we were wrong about our KNN model. The random forest, despite the relative rigidity of tree models, did much better than our KNN model. This is likely thanks to the aggregation of the trees which gives our random forest the ability to classify based on many more variations of the model than a KNN has access to.

It's possible that we could improve upon the KNN using various methods of finding the optimal K, we did alter the K used for the model and found that K=5 gave us the best out of sample error but usually K=5 when dealing with a dataset of this size is an example of overfitting. Because of this we are not confident that the KNN model is the best model to use.

## Question 6 - Association Rule Mining

Here we look at a data set containing 9835 different baskets of groceries purchased while shopping to hopefully discover some insightful associations between groceries in these baskets.

After cleaning the data, we can run it through an apriori algorithm to evaluate association rules between individual grocery items. Apriori returns 1582 total rules.

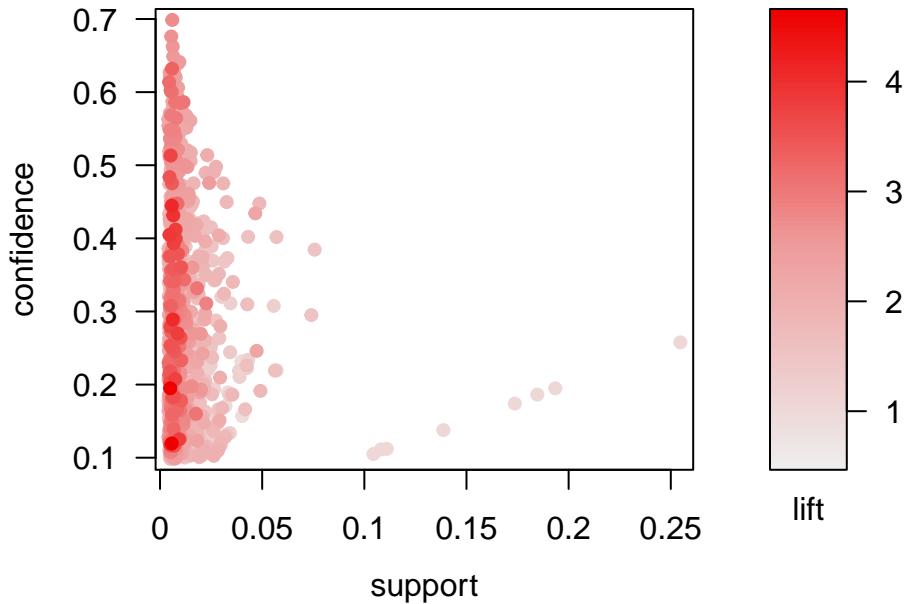
Now we can look at some of individual the association rules. We are most interested in associations with a relatively high confidence (how often one food item appears in transactions that contain another given item(s)), and high lift (measure of the chances a customer will buy one food item if the customer has already bought another given item(s)).

A lift greater than 1 implies an increase in purchase probability between two sets of items. The maximum lift of all the rules we've generated is 4.63, with the maximum confidence being .7 so we will want to look at a subset in that upper range. We can look at a subset of rules with confidence greater than .45 and lift greater than 3. 10 rules fall into this subset:

These association rules generally make intuitive sense. Vegetables are associated with purchases of other vegetables, fruit with yogurt, etc. We also notice that some of these categories are quite vague and thus might be more widely associated with many other categories (i.e. "other vegetables").

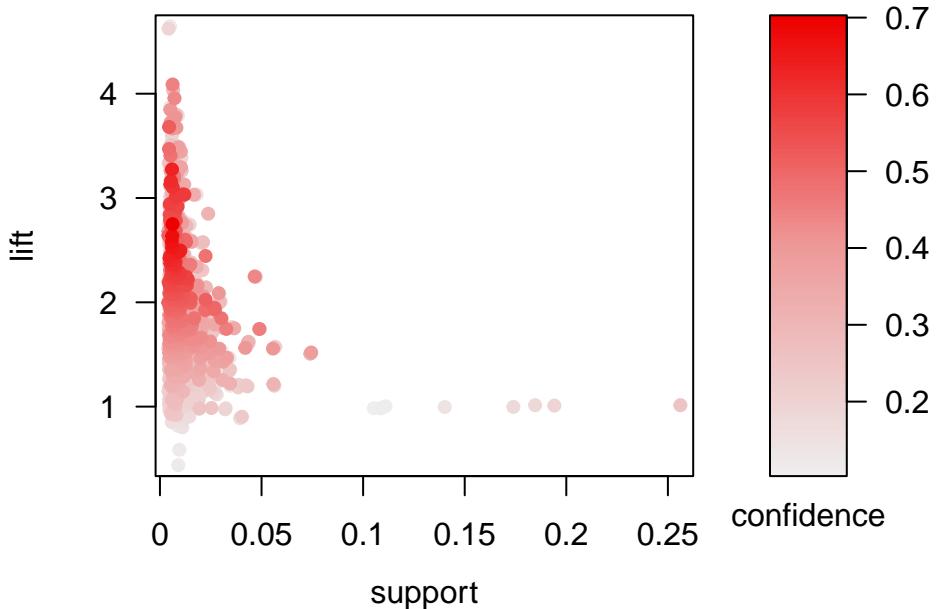
We can plot the rules together in a Confidence vs. Support as well as a Lift vs. Support plot:

### Confidence vs. Support



```
## To reduce overplotting, jitter is added! Use jitter = 0 to prevent jitter.
```

### Lift vs. Support



From these plots, we can see a subset of the association rules that have a relatively high support but low lift and confidence. We can look at this subset by limiting our rules to those with a support greater than 0.04.

They are shown below:

The rules with high support (fraction of grocery carts that contain both items on the left and on the right) tend to involve items that are extremely popular in general (milk, yogurt, other vegetables). This makes sense as to why they frequently have high support but low lift.

Finally, we can visualize a network of the association rules generated by the apriori algorithm. From this magnificent plot we can infer that there are a few central items that are closely related to almost everything else in the grocery store including: whole milk, other vegetables, yogurt, and root vegetables. We also see some items of secondary importance such as sausage, whipped cream, and eggs.

All in all these rules make very much intuitive sense when we consider items that are traditionally popular at grocery stores.

