Final Exam

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GitHub Link to RMD File:

Probability Practice

Part A: Rule of Total Probability: P(A)=P(Y1)*P(Q1|Y1)+P(Y2)*P(Q2|Y2)

Let P(Y) as 65%, P(Q1|Y1)=0.5(Random clickers would click either one with equal probability) and P(Y1)=0.3 0.65=0.3*0.5+0.7*P(Q2|Y2) P(Q2|Y2)=5/7

Par B: Let's use the Bayes Rule We are finding P(D|p)=P(D,p)/P(p)

What is the possibility that someone tests positive–> 0.000025*0.993+(1-0.000025)*0.0001 =0.0001248225=P(p) 0.000025=P(D) What is the possibility that someone tests positive and has the disease–> P(D,p)=P(D)*P(p)= *0.000025*0.0001248225=3.120563e-09

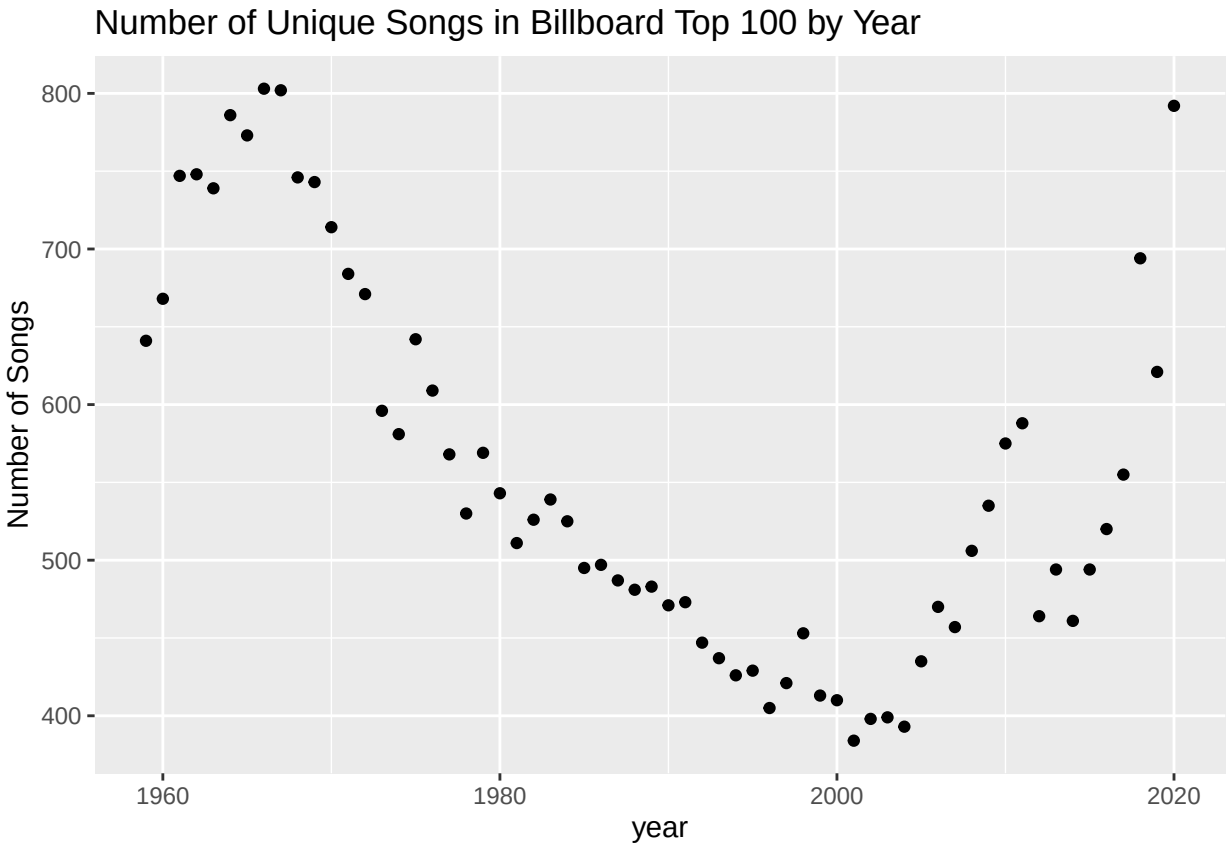
P(D|p)=P(D,p)/P(p)= 3.120563e-09/0.0001248225= 2.5e-05

Wrangling the Billboard Top 100

A

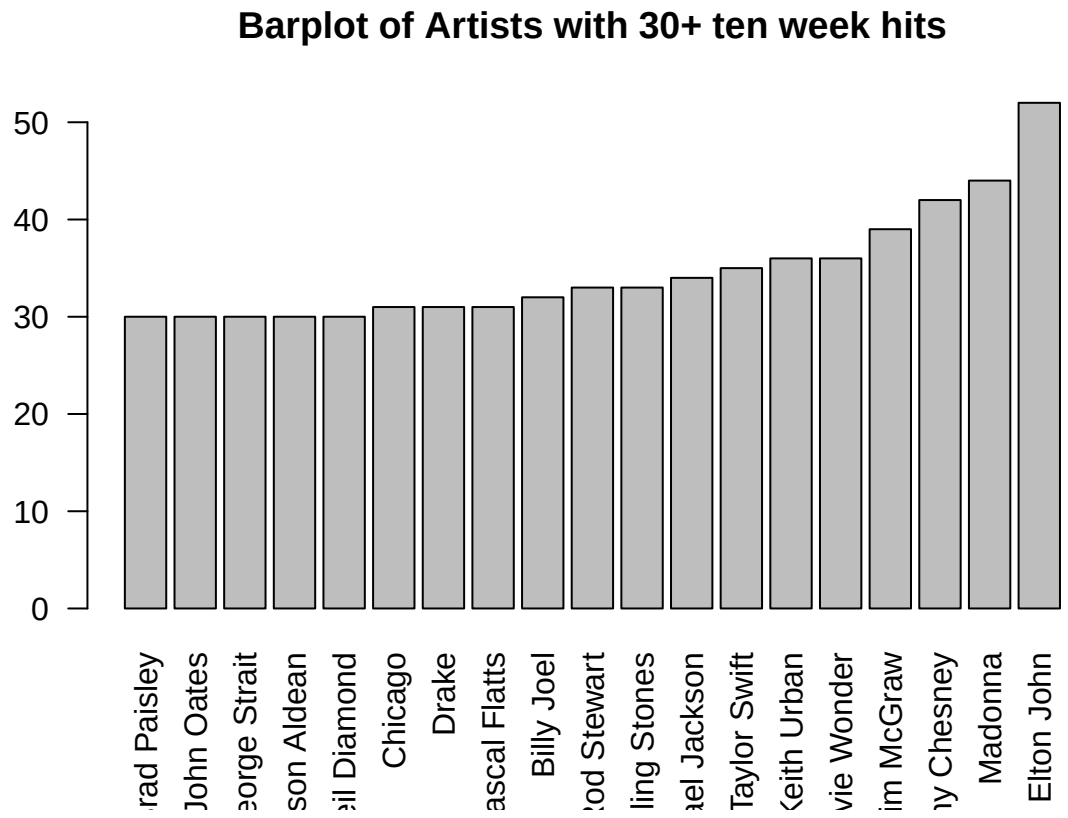
```
## # A tibble: 20 x 3
## # Groups:   song [20]
##    song                                 performer                          count
##    <chr>                                <chr>                              <int>
##  1 Radioactive                          Imagine Dragons                     3828
##  2 Sail                                 AWOLNATION                          3160
##  3 Blinding Lights                      The Weeknd                          2926
##  4 I'm Yours                            Jason Mraz                          2926
##  5 How Do I Live                        LeAnn Rimes                         2415
##  6 Counting Stars                       OneRepublic                         2346
##  7 Party Rock Anthem                    LMFAO Featuring Lauren Bennett & G~  2346
##  8 Foolish Games/You Were Meant For Me  Jewel                               2145
##  9 Rolling In The Deep                  Adele                               2145
## 10 Before He Cheats                     Carrie Underwood                    2080
## 11 Ho Hey                               The Lumineers                       1953
## 12 I Hope                               Gabby Barrett Featuring Charlie Pu~  1953
## 13 You And Me                           Lifehouse                           1953
## 14 Circles                              Post Malone                         1891
## 15 Demons                               Imagine Dragons                     1891
## 16 Macarena (Bayside Boys Mix)          Los Del Rio                         1830
## 17 Need You Now                         Lady Antebellum                     1830
## 18 All Of Me                            John Legend                         1770
## 19 Somebody That I Used To Know         Gotye Featuring Kimbra              1770
## 20 How To Save A Life                   The Fray                            1711
```

B



We wanted to determine if musical diversity (ie. the number of unique songs in a given year) has changed with time. We have thus plotted the number of unique songs for each year. We see that the number of unique songs in 1959 is about 640. It then generally increases to 800 at around 1967, only to then begin decreasing drastically, till around 2001, where it bottoms out below 400. Finally, starting at around 2003, it increases rapidly, until the most recent year of 2020, where it is again almost at 800.

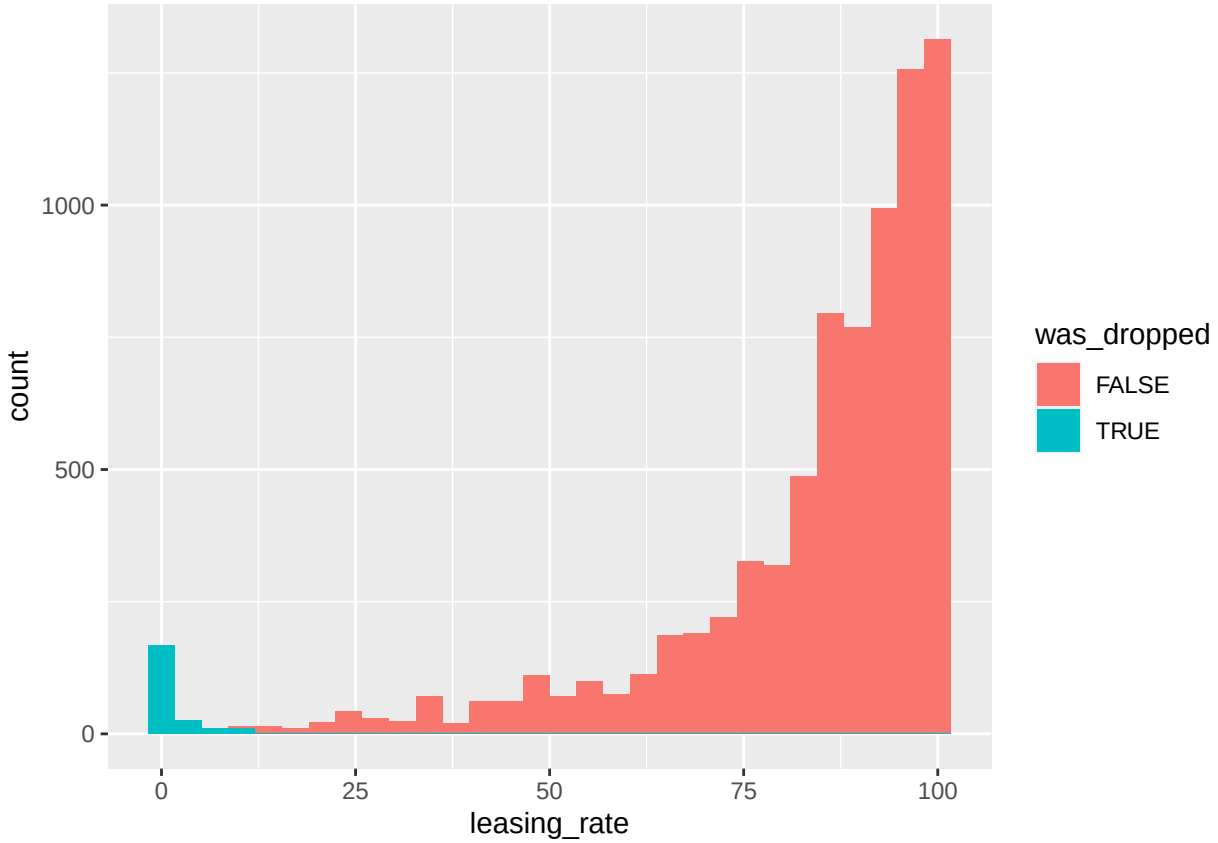
C



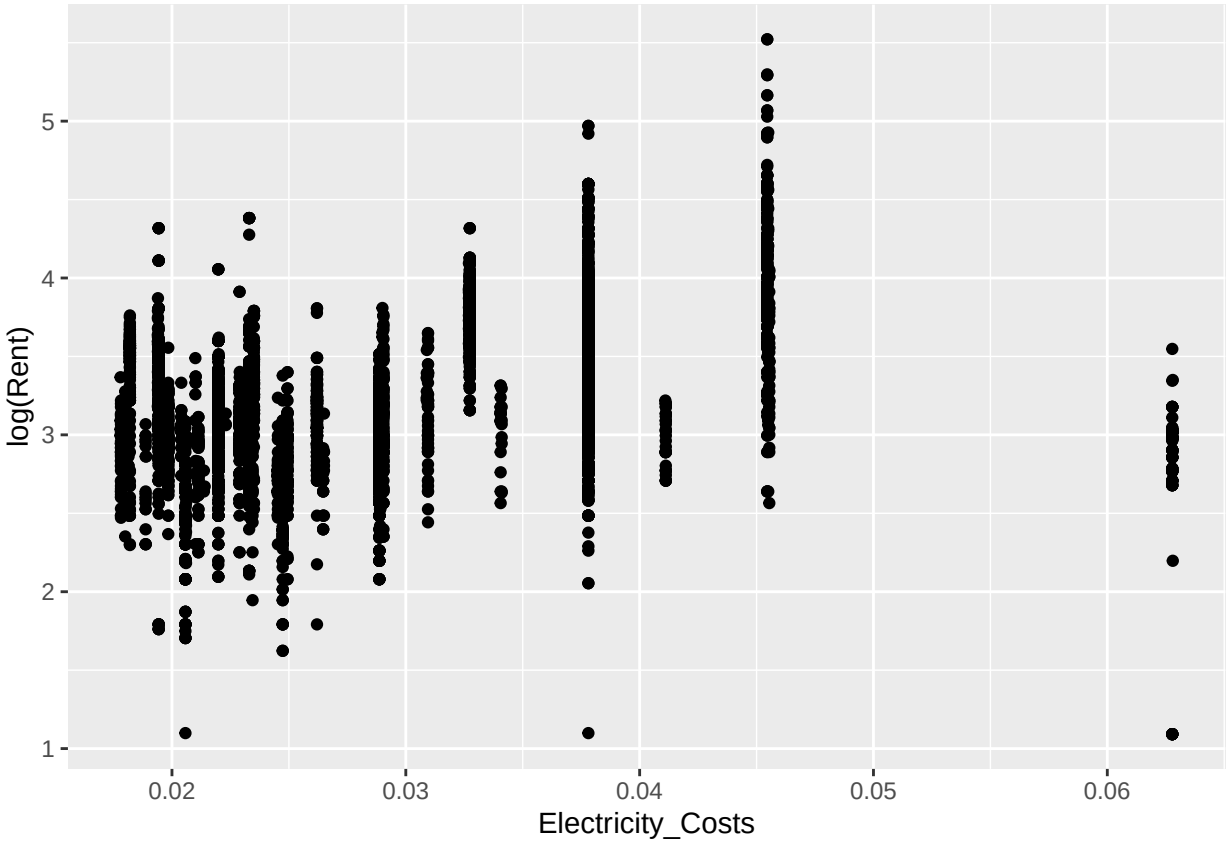
Well, Elton John has obviously the highest number of songs that have ten weeks hit. And total of 19 singers have 30 or more ten weeks hit songs. Except Elton John, Tim McGraw, Michael Jackson and Madonna are also among the top tier of the list. Quite interesting is that, I never heard of Tim McGraw in Taiwan!!

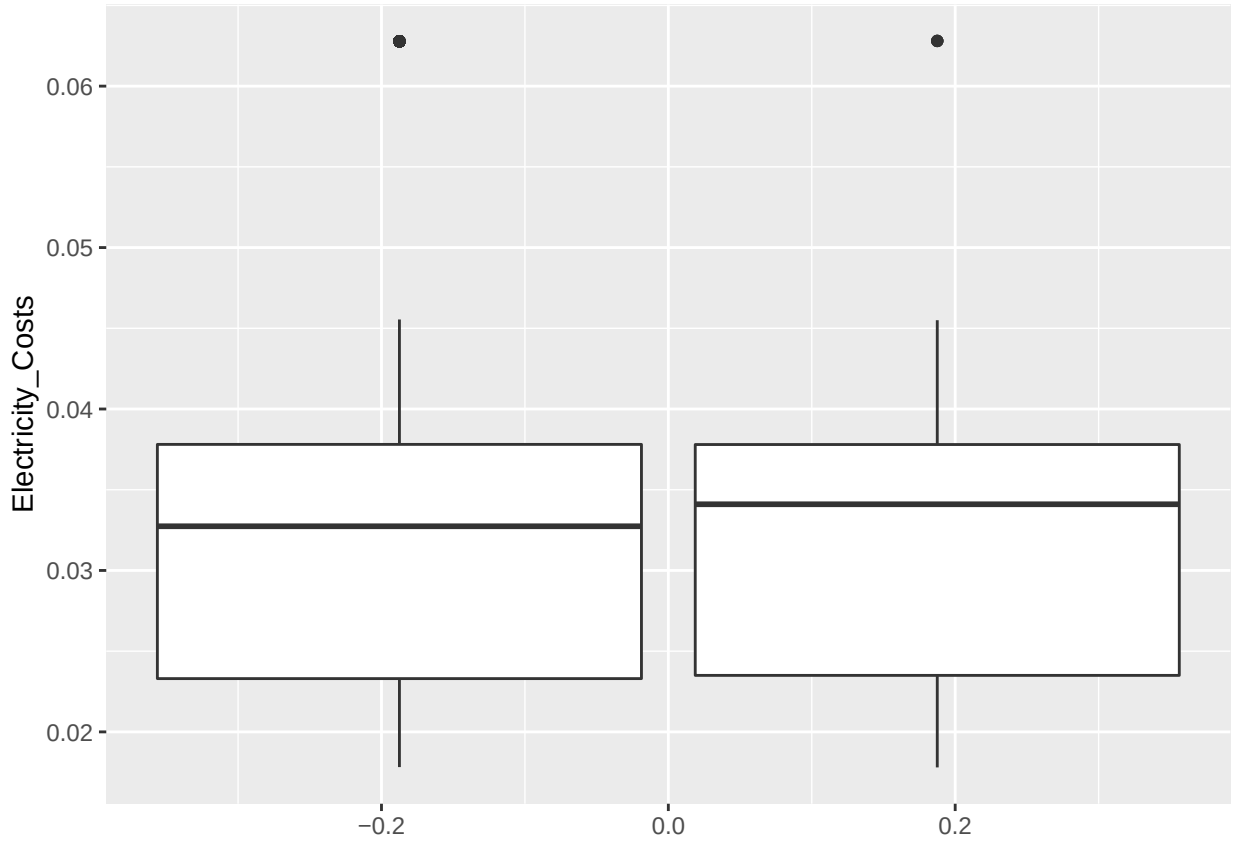
Visual Story Telling Part 1: Green Buildings

We first begin with dropping the low occupancy building. While the below histogram does agree that there appears to be an outlying cluster of low occupancy buildings. These are likely un-representative of our new building, as it is being built in Austin, where housing is lacking. However, we choose not to omit them, as we prefer to have as much data in our analysis as possible, and we cannot be sure that they will hurt our analysis. We can model only on the high occupancy buildings, and see if that performs the accuracy of our model, yet this again assumes that we know ahead of time that our building won't be one of these low occupancy buildings, which we cannot be 100% certain that it will be.



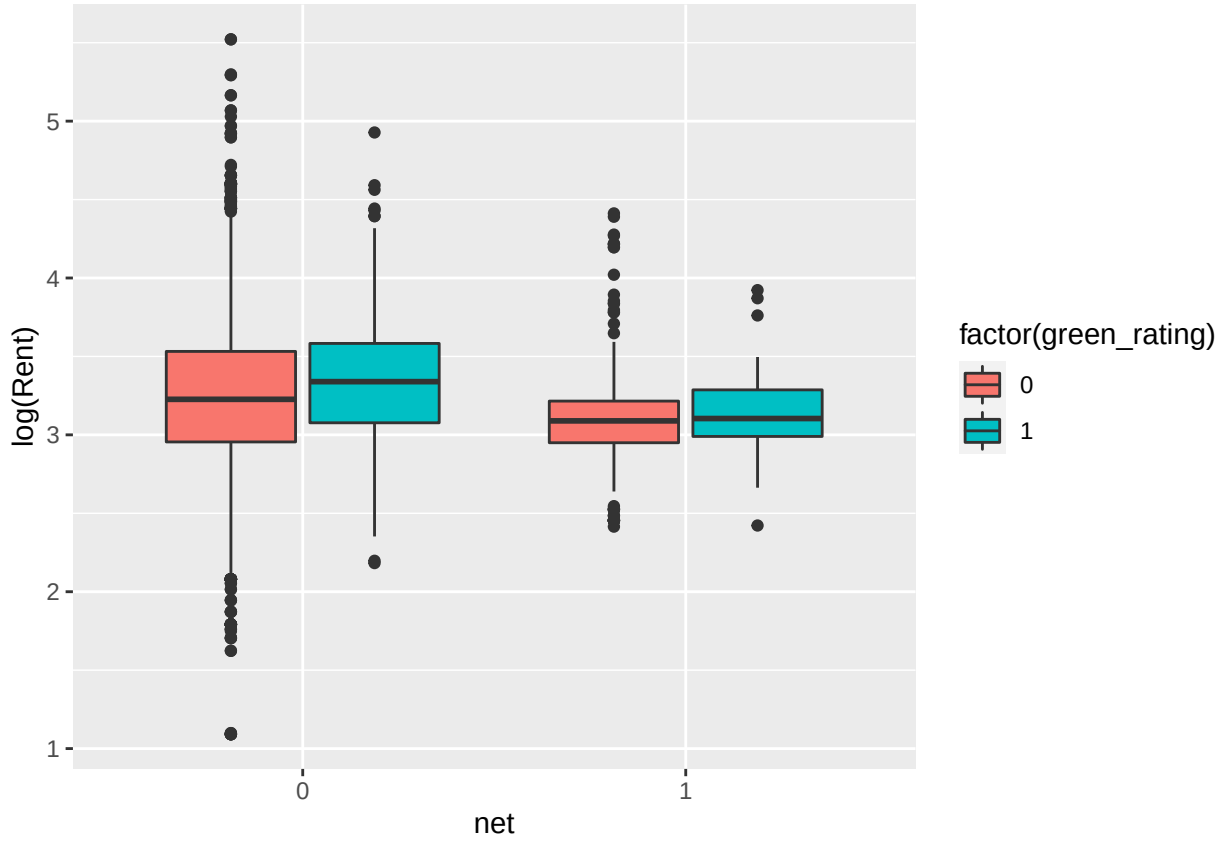
Next, we move on to the stats guru's rent predictions. He first assumes that there are no confounding variables between the interaction between rent and green status. For instance, since one of the main advantages of green buildings is lower energy usage, we might expect that green buildings are more enticing to builders in high energy cost areas. We see this in the boxplot below, where green rating buildings have on median a greater electricity cost then non-green-rated buildings. High electricty cost buildings also tend to have greater rents however, as seen in the dotplot below, perhaps because these costs are passed down to consumers, or just that prices tend to be higher in higher energy cost areas, due to general wealth.


log(Rent)
5
4
3
2
1
0.02
0.03
0.04
0.05
0.06
Electricity_Costs



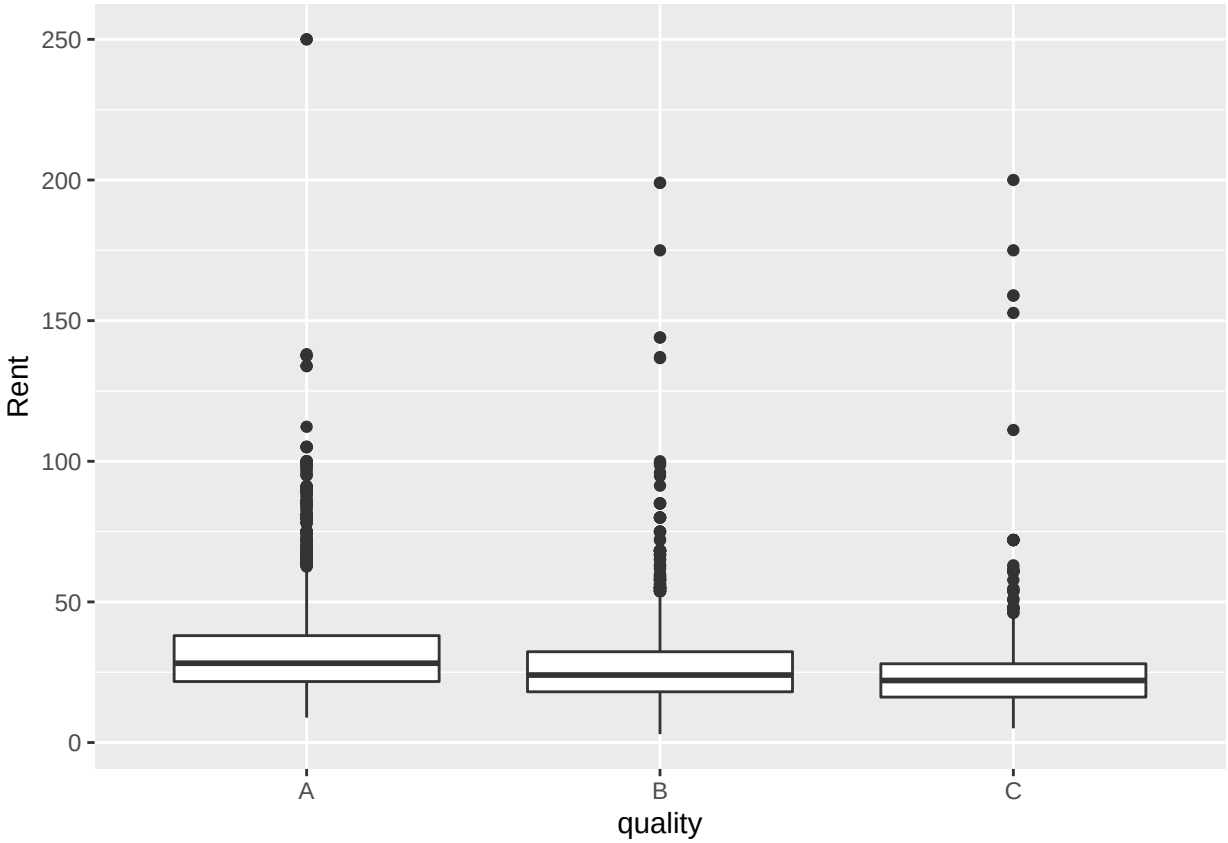
We could try and take this variable into account in a more advance regression model. We could also account for facts about the area by predicting rent-cluster_rent, or in other words how much higher rent green buildings are than non-green_buildings in each given area.

Another important fact unaccounted for by the model is that some buildings charge their individuals for utilities, while others do not. Charging for utilities separate from rent is called a net contract. We see in the below boxplot that green_rating and net contracts have some interaction, (ie. In buildings where utilties are charged for, rent is on median the same, regardless of whether the building is green rated. However in non net contract apartments, green rating buidlings come at a premium). We should use this to note that perhaps green rated buildings are more profitable when they are not on a net contract, and we can perhaps expect a higher premium if we place users on a net contract.



Another area where we could see other variables taken into account is building quality. As we see, green buildings are disproportionately good, and good buildings have higher rents. This variable however is difficult to fully take into account, as a building being green contributes to the quality of the building.

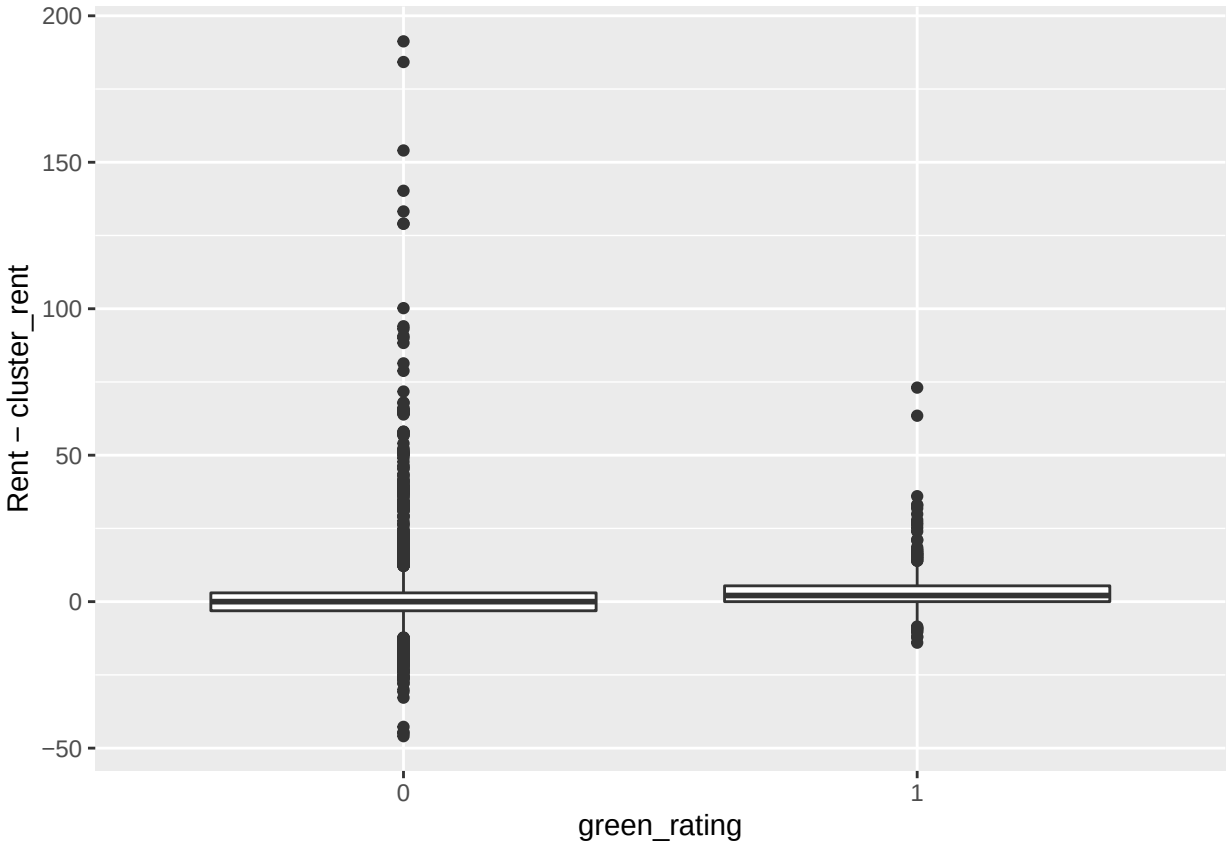
```
##
##        0    1
##   A 2611  546
##   B 3495  132
##   C 1103    7
```



One way we can try to account for these things is rather than looking at how much rent

We also note that the stats wizard makes that rent and occupancy rate are not related. If rents are too high or low, it might lead to changes in occupancy rate. It would be perhaps better if we predicted revenue, ie. rent * occupancy * square footage, rather than just rent, and asusming occupancy is fixed.

Overall, it is difficult to fix many of these issues without running advanced statistical models. However, one quick fix is assuming that non-green factors a buildings is a function of proximity, ie. if one thing is affecting a building's rent, then it is likely effecting the rent of nearby buildings as well. Thus, our modeling for how much green buildings may charge in extra rent is how much more rent it charges then the average rent of those building's in it's cluster. Note that each cluster contains 1 green certified building, and many non-green certified building, meaning that we need not worry about our clustering placing all green buildings together, and thus not detecting the green-building premium. The results of this clustering is seen below.



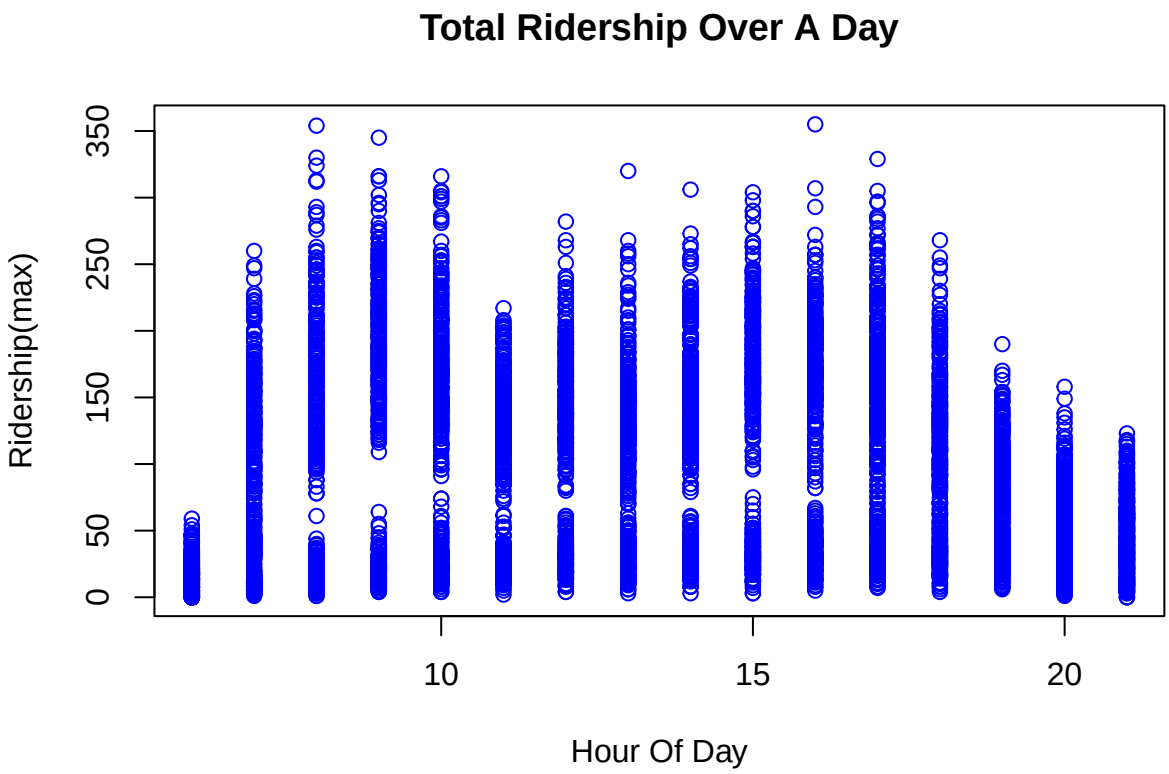

```
## [1] "Excess Rent: 2.41245805577578"
```

```
## # A tibble: 2 x 4
##   green_rating  Rent cluster_rent excess_rent
##   <fct>        <dbl>        <dbl>       <dbl>
## 1 0             28.3         27.6       0.712
## 2 1             30.0         26.9       3.12
```

Here, we see green rating has an excess rent of 3.1244 in dollars per square root per year, as compared to the default 0.712's excess rent. We thus replace the \$2.6 number with \$2.41. Repeating their arithmatic is left as an excercize to the grader :)

Capital Metro Data

For each hour in the day, we look at the ridership.



From the plot we can see that the ridership were initially low at the beginning of a day (6am), as the commute time starts, which is around 7am - 10am, the ridership goes up fast. And then it starts to drop after 10 am, which most students have all gone to school. At 4pm, students are off school and the ridership increases till 6pm.

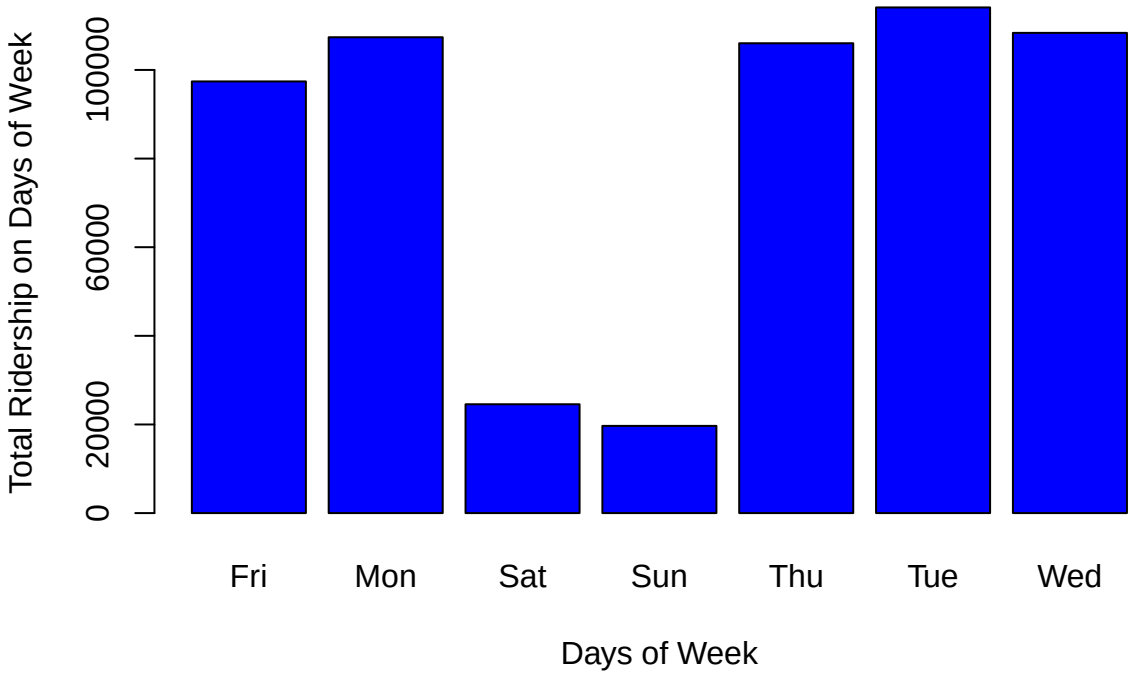
Next, combine the month and day of month.

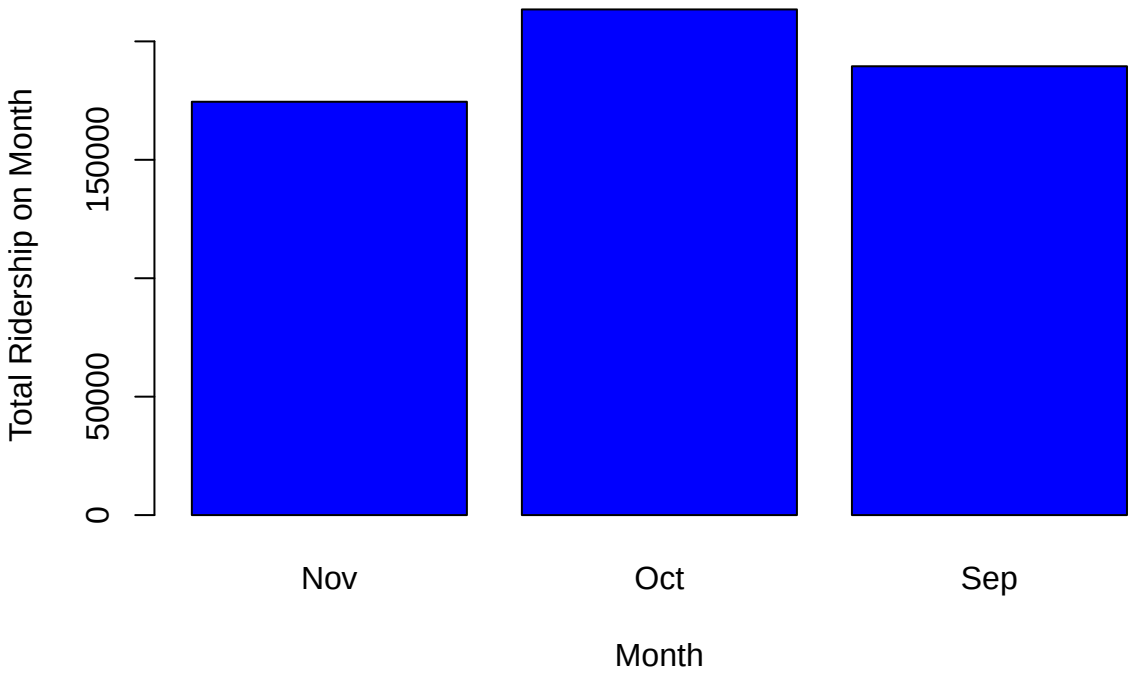
```
##    df2$day_of_week df2$month df2$Total_ridership
## 1              Fri       Nov                32162
## 2              Mon       Nov                34055
## 3              Sat       Nov                 6890
## 4              Sun       Nov                 5608
## 5              Thu       Nov                35001
## 6              Tue       Nov                32824
## 7              Wed       Nov                27969
## 8              Fri       Oct                31898
## 9              Mon       Oct                44724
## 10             Sat       Oct                 8123
## 11             Sun       Oct                 6643
## 12             Thu       Oct                34682
## 13             Tue       Oct                44229
## 14             Wed       Oct                43190
## 15             Fri       Sep                33343
## 16             Mon       Sep                28593
## 17             Sat       Sep                 9543
## 18             Sun       Sep                 7424
## 19             Thu       Sep                36340
## 20             Tue       Sep                37051
```

```
## 21             Wed       Sep               37204
```

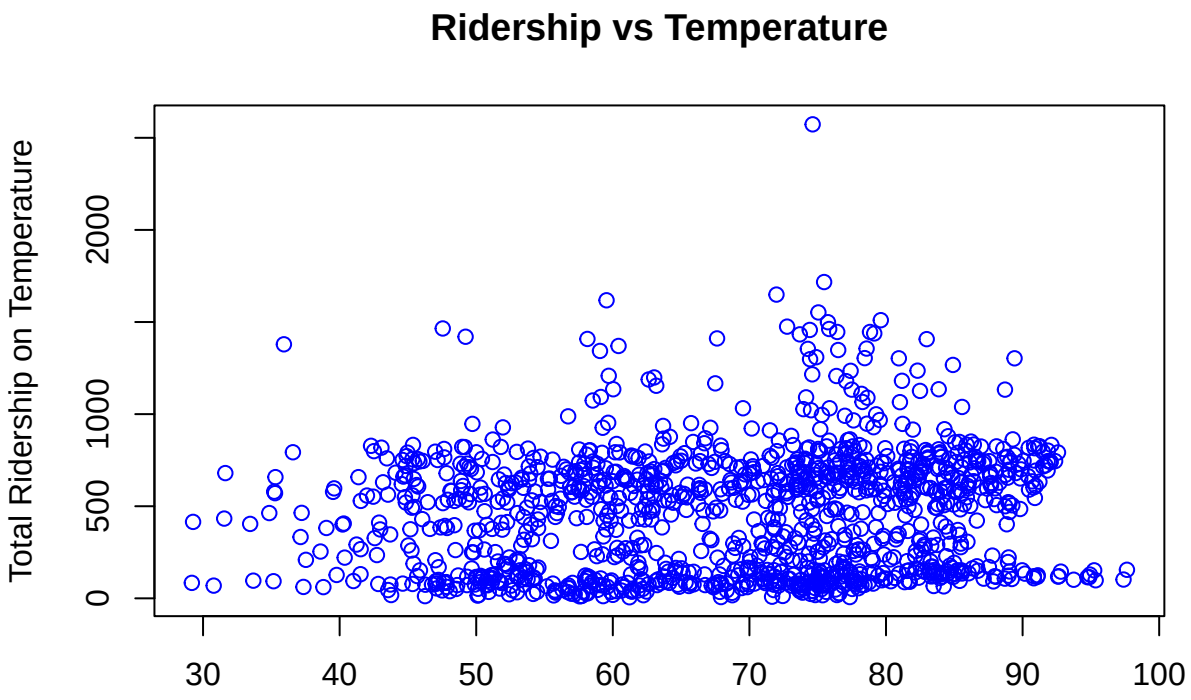
```
##   df2$month df2$Total_ridership
## 1       Nov              174509
## 2       Oct              213489
## 3       Sep              189498
```

```
##    df2$month df2$day_of_week df2$Total_ridership.x df2$Total_ridership.y
## 1        Nov             Fri                  32162                 174509
## 2        Nov             Mon                  34055                 174509
## 3        Nov             Sat                   6890                 174509
## 4        Nov             Sun                   5608                 174509
## 5        Nov             Thu                  35001                 174509
## 6        Nov             Tue                  32824                 174509
## 7        Nov             Wed                  27969                 174509
## 8        Oct             Fri                  31898                 213489
## 9        Oct             Mon                  44724                 213489
## 10       Oct             Sat                   8123                 213489
## 11       Oct             Sun                   6643                 213489
## 12       Oct             Thu                  34682                 213489
## 13       Oct             Tue                  44229                 213489
## 14       Oct             Wed                  43190                 213489
## 15       Sep             Fri                  33343                 189498
## 16       Sep             Mon                  28593                 189498
## 17       Sep             Sat                   9543                 189498
## 18       Sep             Sun                   7424                 189498
## 19       Sep             Thu                  36340                 189498
## 20       Sep             Tue                  37051                 189498
## 21       Sep             Wed                  37204                 189498
```


Total Ridership on Days of Week
0
20000
60000
100000
Fri
Mon
Sat
Sun
Thu
Tue
Wed
Days of Week



From the two bar plots we wouldn't say that there is obvious patterns on the three months we have. We can say that October has the highest total ridership while November has the lowest.But there is clearly a pattern on weekdays. Weekdays have much more riderships than weekends and Fridays have fewer ridership compare to other days. That might be some colleges, like us MSBA program, don't have lectures on Friday.



A plot showing no clear trend between ridership numbers and temperature

There is no obvious pattern between temperature and total ridership.

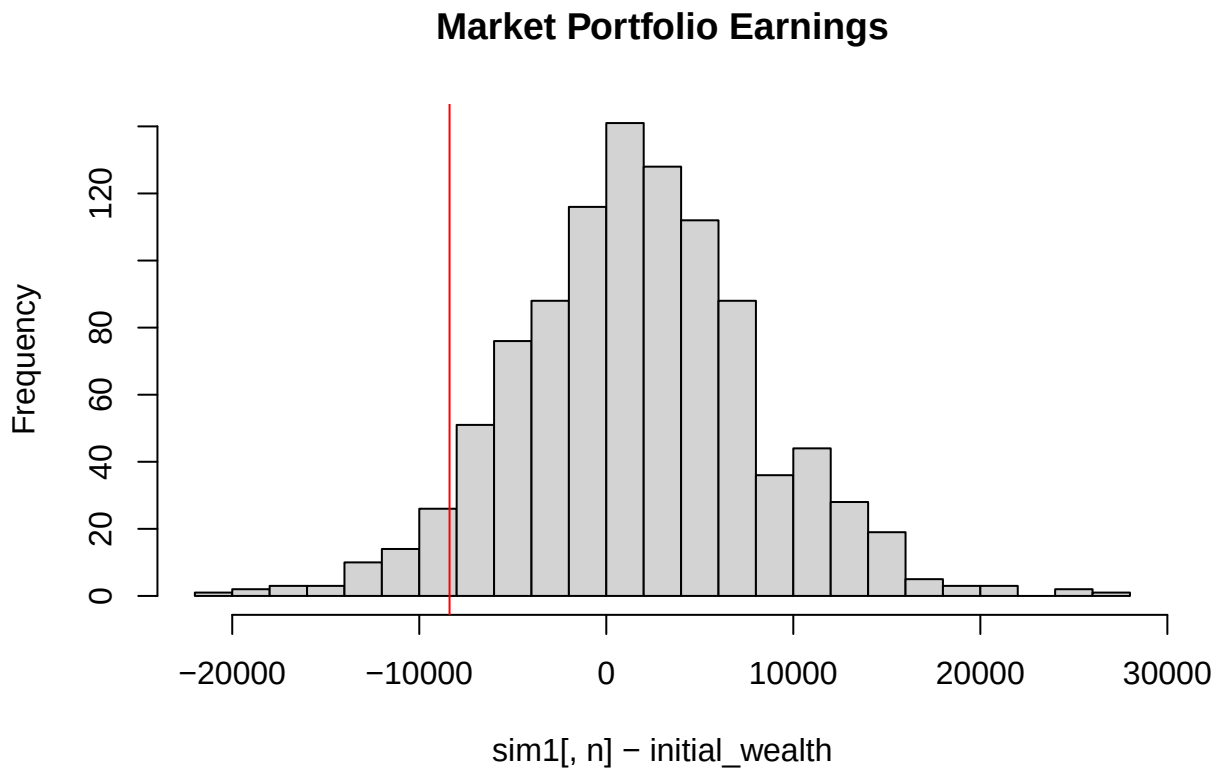
Portfolio Modeling

Portfolio 1: Market

Portfolio 1 is built to act like the market, using etf's that each are meant to track the market.

- **33% SPY** ETF designed to track S&P 500
- **33% QQQ** ETF that tracks NASDAQ-100
- **33% IWM** iShares Russell 2000 ETF, tracks 2000 small cap companies

We know plot the bootstrap distribution of change in wealth, as well as the VaR of 0.05



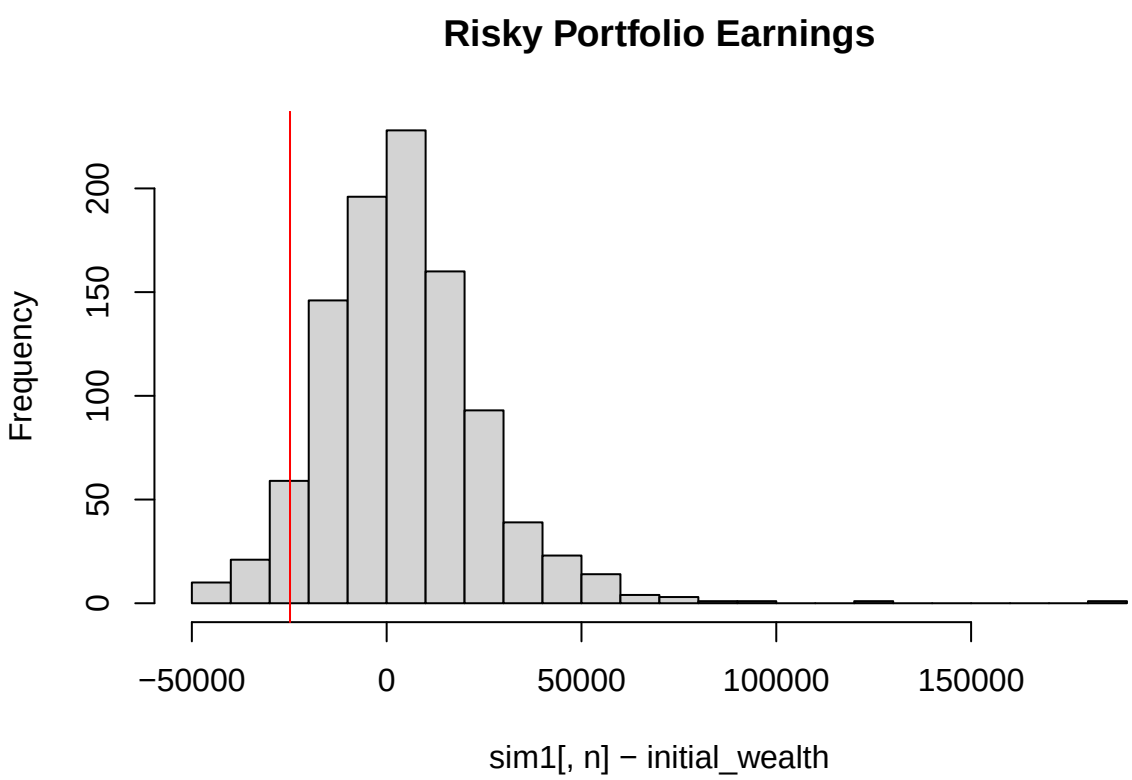

```
##        5%
## -8381.143
```

Here, VAR of 5% is a loss of 8381$, or about an 8.4% negative return.

Portfolio 2: "High Betas"

Portfolio 2 takes some of the highest beta etf's to maximize risk and return.

- **25% TQQQ** ETF designed to triple returns of NASDAQ-100
- **25% OIH** Oil ETF
- **25% FAS** Designed for 3x return of RUssell 1000
- **25% LABU** Designed to perform 3x S&P Biotech.




```
##        5%
## -24801.75
```

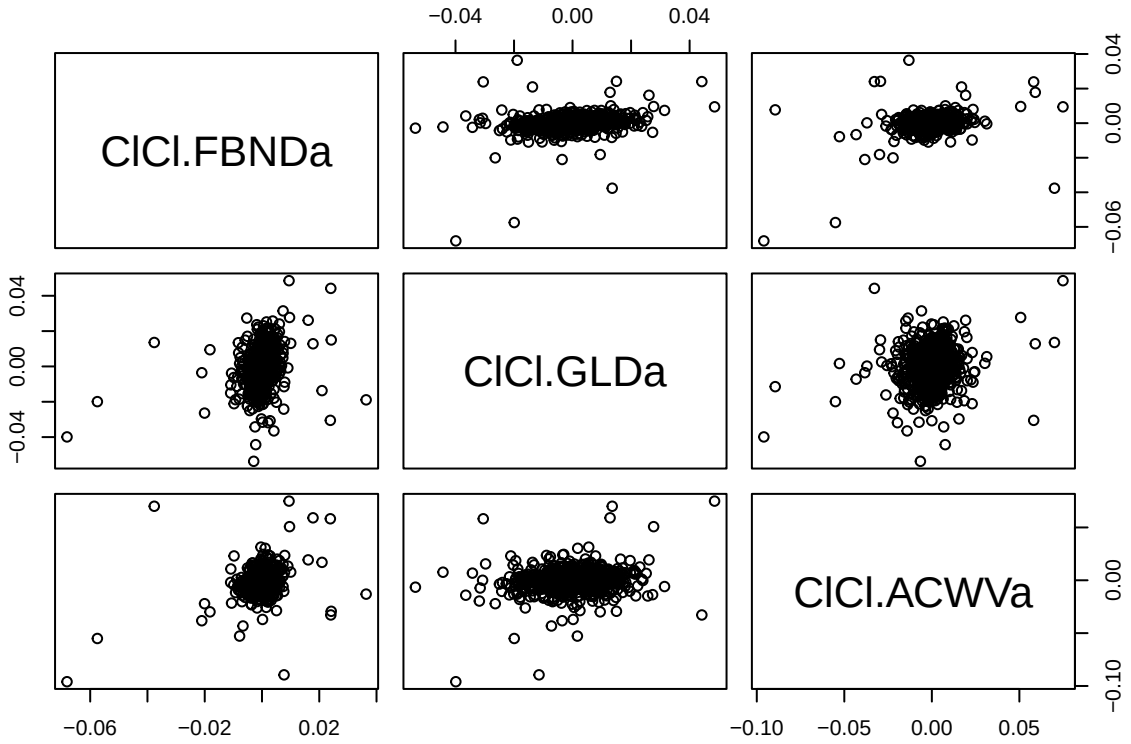
Here, losses are much larger, at negative 24,800

Portfolio 3: Low Beta ETF

Lastly, we use ver low beta etfs to try and underperform the market at lower risk

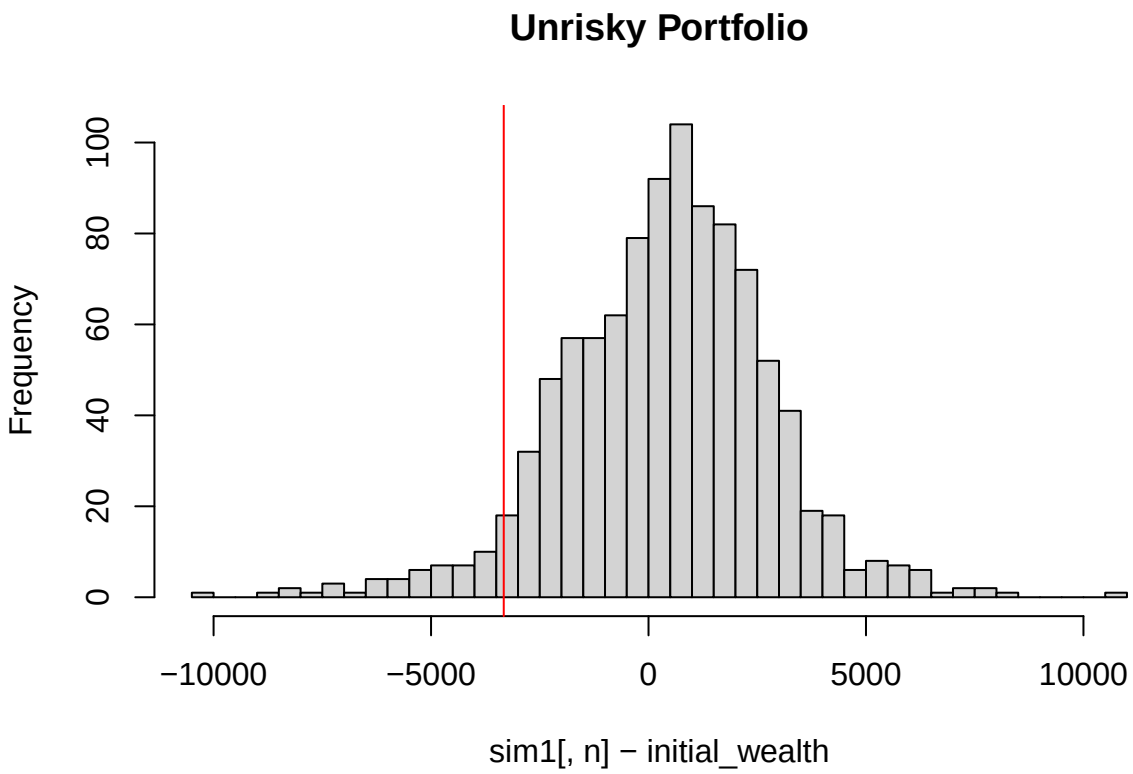
- **33% FBND** ETF of many bonds
- **33% GLD** Gold Shares
- **33% ACWV** Global equity market ETF

```
## [1] "FBND"
## [1] "GLD"
## [1] "ACWV"
```



From the pairs correlation matrix, we see that these Bond ETFs are less correlated than the ETFs in Portfolio 1 but higher than Portfolio 2.

Then, we simulate the 20-day trading period of this portfolio.



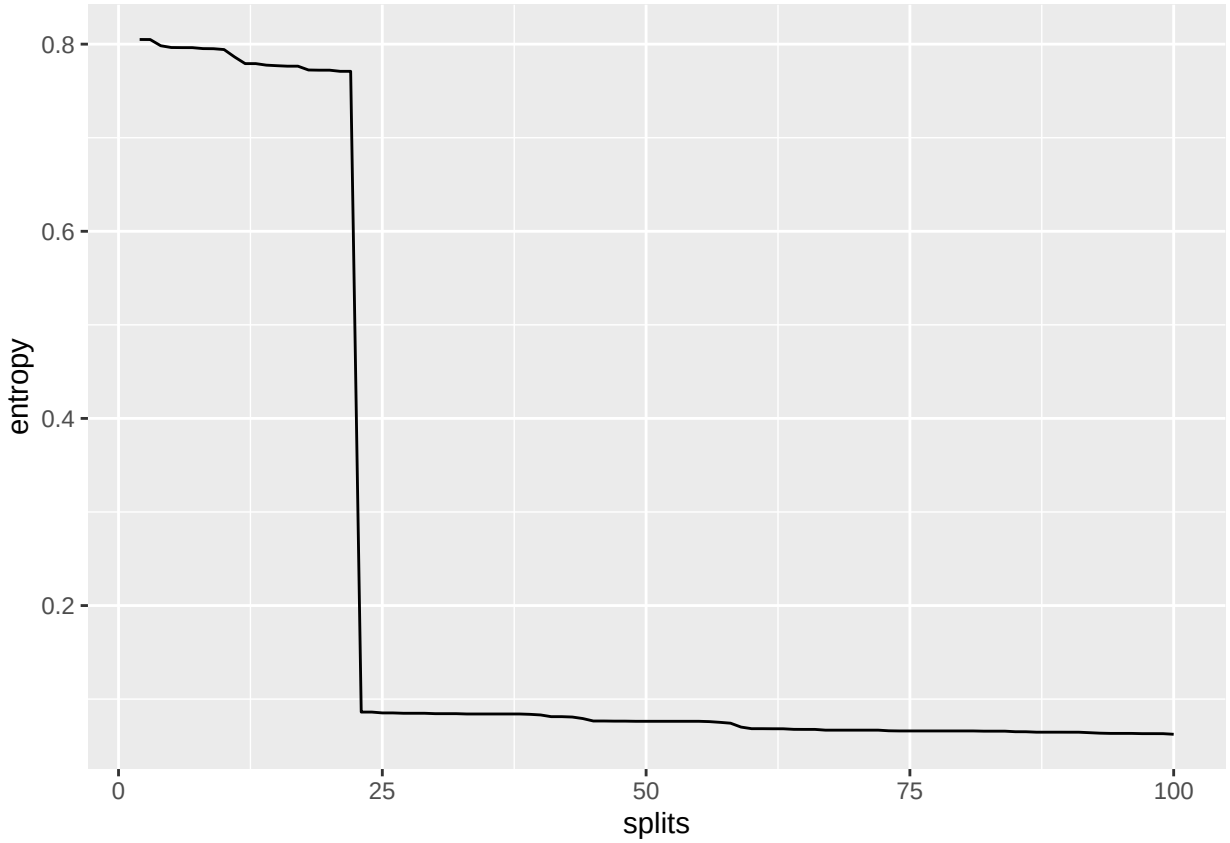

```
##       5%
## -3328.81
```

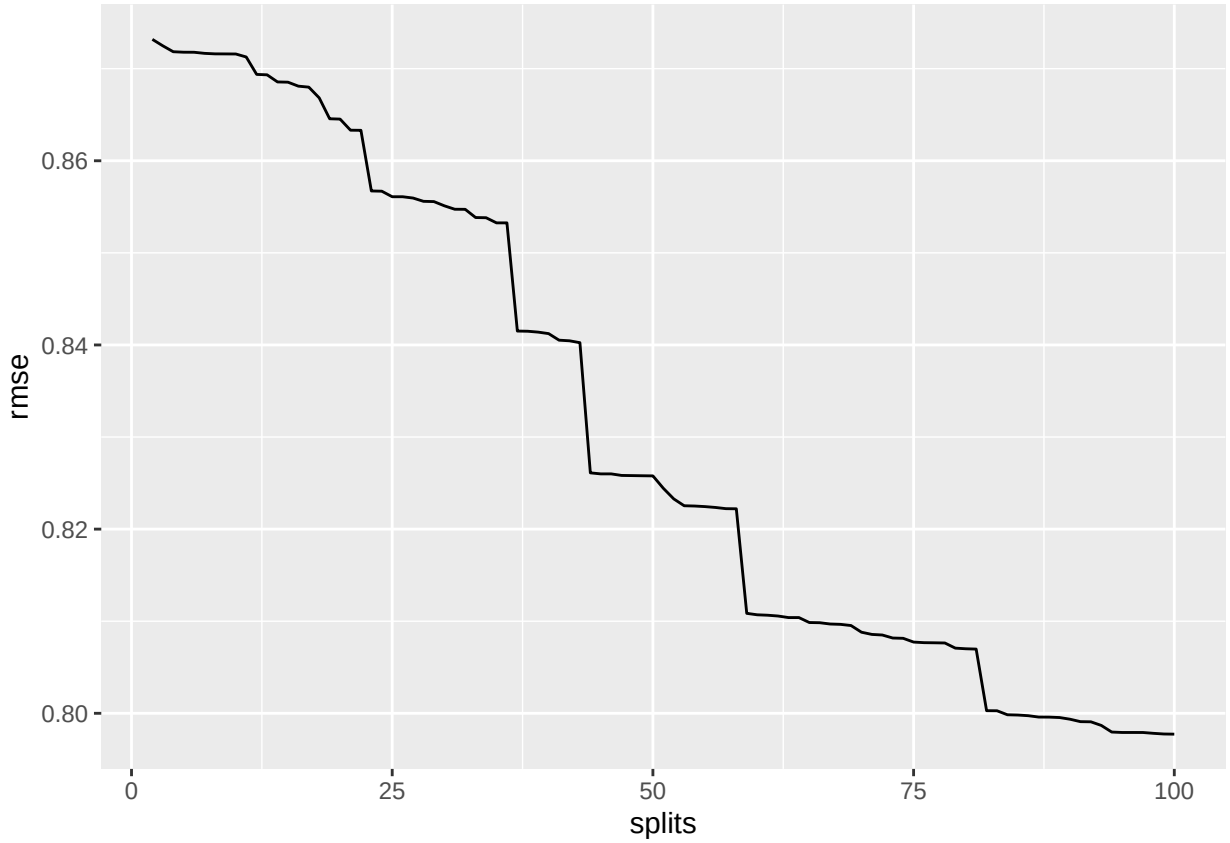
Here, we see the smallest loss of -3328.81

In conclusion, we saw what we expected. The low beta etf of bonds and gold had very low VAR, at a 3.23% loss, the very risky portfolio of high leverage etf's had a much higher VAR of about a 25% loss, and the in market indices lied somehwere in between at around an 8.4% loss.

Clustering and PCA

We first attempt hierarchical clustering. To judge how well the hierarchical clustering and how it's picked up on the wine and beer, look at the rmse of taste and the entropy of type of wine in the hierarchical tree at various numbers of splits, as seen below.

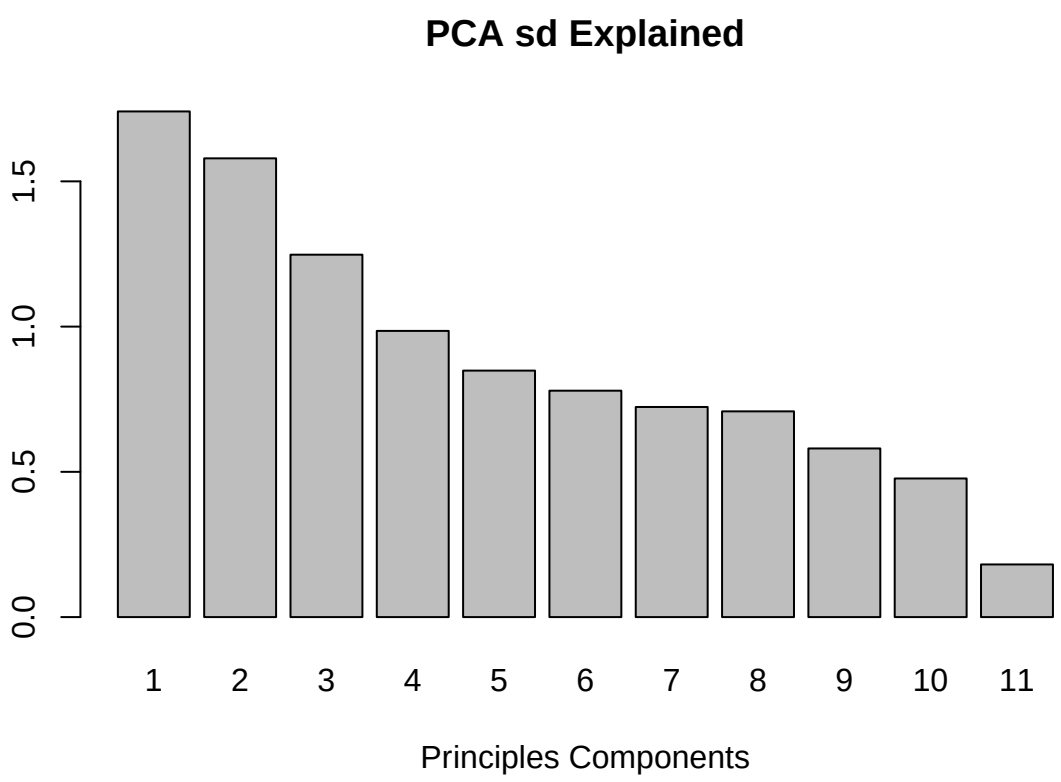





```
## [1] 6497
```

Here, we see that there is a significant drop in entropy at the 22nd split, implying that this split divides a large number of red and white wines. This is unlikely to be simply overfitting, as it is a rather significant single drop, and occurs at the 22nd split in a 6000+ entry list. Alternatively, we see a few gentle declines in rmse for quality, implying it is at various splits detecting differences in quality.

We next attempt PCA. We look at how much variance the principal components each explain.



We see that the first 4 principle components do most in explaining the data, while the other's do much so, and we thus choose to only view the first 4 principal components.

```
##                              PC1         PC2         PC3         PC4
## fixed.acidity        -0.23879890  0.33635454 -0.43430130  0.16434621
## volatile.acidity     -0.38075750  0.11754972  0.30725942  0.21278489
## citric.acid           0.15238844  0.18329940 -0.59056967 -0.26430031
## residual.sugar        0.34591993  0.32991418  0.16468843  0.16744301
## chlorides            -0.29011259  0.31525799  0.01667910 -0.24474386
## free.sulfur.dioxide   0.43091401  0.07193260  0.13422395 -0.35727894
## total.sulfur.dioxide  0.48741806  0.08726628  0.10746230 -0.20842014
## density              -0.04493664  0.58403734  0.17560555  0.07272496
## pH                   -0.21868644 -0.15586900  0.45532412 -0.41455110
## sulphates            -0.29413517  0.19171577 -0.07004248 -0.64053571
## alcohol              -0.10643712 -0.46505769 -0.26110053 -0.10680270
```

Here, the first principal components seems to be detecting high sulfur dioxide wines. This would explain why these wines are lower ph, as sulfur dioxide is acidic according to google. This also perhaps explains why these wines are lower in other types of acidity, as they are more acidic due to the sulfur dioxide.

Principal component 2 appears to show very dense very low acohol content wines.

Principal component 3 seems to see low citric acid high ph wines. Citric acid according to google citric acid is relatively weak, and thus likely explains why it has higher ph than other wines.

Lastly, PC 4 seems to detect low sulphate low ph wines, which is detecting what I just said.

We check how much these PC detect quality and different qualities by seeing how well they can be used as a linear model for quality and a logistic regression for wine taste.

```
##
## Call:
## lm(formula = quality ~ pca$x[, 1] + pca$x[, 2] + pca$x[, 3] +
##     pca$x[, 4])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6624 -0.5093 -0.0559  0.5324  3.5263
##
## Coefficients:
##              Estimate Std. Error t value             Pr(>|t|)
## (Intercept)  5.818378   0.009822  592.39 < 0.0000000000000002 ***
## pca$x[, 1]   0.038202   0.005643    6.77       0.000000000014 ***
## pca$x[, 2]  -0.174166   0.006220  -28.00 < 0.0000000000000002 ***
## pca$x[, 3]  -0.150821   0.007874  -19.16 < 0.0000000000000002 ***
## pca$x[, 4]  -0.146175   0.009970  -14.66 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7917 on 6492 degrees of freedom
## Multiple R-squared:  0.1786, Adjusted R-squared:  0.1781
## F-statistic: 352.9 on 4 and 6492 DF,  p-value: < 0.00000000000000022
```

```
## [1] 0.987071
```

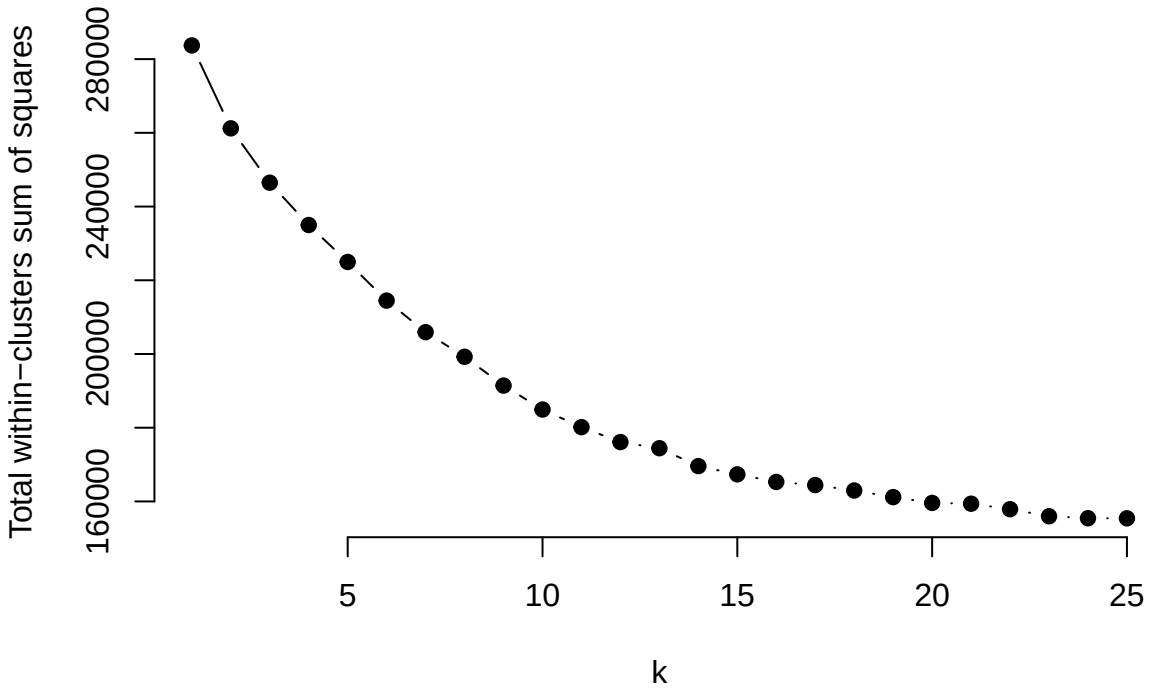
Here, we see that we see that our residual square error is relatively high still at 0.781, with R-square of only 0.1786. However, this is not that much better than our other data. We see that it is very good at accessing color however, at 98.7/% accuracy using only the first 4 pc.

Ultimately, we believe PCA makes more sense on our data. This is for the primary reason that many of the measures are very highly correlated with one another. The amount of free vs total sulfur dioxide will obviously be related, as one is a subset of the other, and the amount of each acid will affect the ph of the wine. While these issues might hurt clustering, causing some extraneous factors effect creating useless sparsness in clustering, PCA is designed for these exact scenarios in mind.

Market segmentation

Our method will be using kmeans to cluster the data, and observe the results. We first begin by cleaning our data, scaling it and reindexing.

We continue with our data ### Elbow method



The Elbow Plot above indicates a kink at $k = 14$. Although perhaps just a random drop, we choose to select it as our choice k, since it is a point at which wthin sum squares does not appear to decrease much more from further itterating.

Running K-Means with 14 clusters

We now look at the centers of some of the largest clusters.

```
##        chatter current_events       travel photo_sharing uncategorized
## 6   0.07205880     0.27684711  0.288727032   -0.09071828    0.11259854
## 13  1.03583481     0.08209725 -0.044325901   -0.01234994    0.75732750
## 11 -0.01951185    -0.01663479 -0.003362117   -0.20979829    0.23838226
## 3  -0.05609136     0.33853271  0.355535359   -0.01396405    0.45730692
## 1  -0.16479790     0.18220668 -0.006172873   -0.13487751    0.89756950
## 10 -0.03520613     0.25745234  0.028581119    0.14091908   -0.06207133
##        tv_film sports_fandom    politics        food      family
## 6  -0.11619101    0.14065669  0.15052740  0.04049422 -0.05999555
## 13 -0.11117616   -0.15165194 -0.14184117 -0.15346615 -0.10053936
## 11 -0.25368123   -0.13653580 -0.21256295 -0.05838928  0.07013474
## 3   2.76851340   -0.15780317  0.04853353  0.23755311 -0.11029086
## 1   2.13059224   -0.04523218 -0.24417590 -0.05994916 -0.15654764
## 10  0.02067083    2.90549609 -0.12109863  2.60687493  2.03615164
```

```
##    home_and_garden       music          news online_gaming   shopping
## 6       0.23510191  0.01418264 -0.0006901999    0.08935906 -0.2378226
## 13      0.59162058 -0.11600476 -0.1211191143   -0.06961621 -0.1010846
## 11      0.06288968 -0.05894335 -0.1591778016   -0.00482014 -0.2067087
## 3       0.38896740  0.09303865  0.0818640860   -0.19426608  0.1244383
## 1       0.23530864  2.61174292 -0.1511209468   -0.09575482 -0.1038649
## 10      0.35342583  0.20985681  0.0468349705    0.05605539  0.1424614
##    health_nutrition college_uni sports_playing     cooking        eco
## 6       0.050860594  0.12732753     -0.1112904 -0.05898219  0.4479995
## 13     -0.079020000 -0.06397636      0.3197372 -0.13258116  0.1252254
## 11     -0.172020156 -0.14162330     -0.1532389 -0.17080548  0.1782169
## 3      -0.113656707 -0.09678584     -0.1117945 -0.09432379  0.1953218
## 1      -0.208321800  1.14206171      0.4004778 -0.23119930 -0.0596169
## 10      0.002488701  0.01337708      0.2526282  0.10913460  0.4595234
##      computers   business    outdoors      crafts automotive         art
## 6   0.29753290 -0.3460090  0.29780310  0.21793373  0.1245356  0.33167537
## 13  0.01645205  0.4248374  0.07184545  0.41970713 -0.1817836 -0.01789660
## 11  0.08775547 -0.1199295  0.26918780  0.01213724  0.1132163 -0.10000172
## 3  -0.13149986  0.2935722 -0.18224348  1.07451555 -0.1988306  4.20323013
## 1  -0.10741060  0.4773231  0.08713668 -0.01027882 -0.2250684 -0.21581184
## 10  0.23380558  0.2571776  0.01216739  0.98476458  0.3470012  0.08865192
##        religion      beauty   parenting       dating      school
## 6   0.120701794 -0.10070195  0.18658414 -0.009528244  0.09244824
## 13  0.004101468  0.28343247  0.07342746  4.900724879  1.31148861
## 11 -0.170963536 -0.07297489  0.10633422 -0.083600176  0.03933017
## 3  -0.068701593 -0.01688381 -0.19721392 -0.121684662  0.09410364
## 1   0.106066993 -0.01399486 -0.22633690 -0.128772294 -0.28808986
## 10  3.071666149  0.59857470  3.04953832 -0.002792854  2.37092108
##    personal_fitness      fashion small_business        spam       adult
## 6        0.12183236 -0.020449872      0.3142883 12.41886450  3.75022215
## 13      -0.05653418  0.834146963      0.3790624 -0.07768727 -0.08155232
## 11      -0.04852091 -0.147543491      0.4232040 -0.07768727  4.78604639
## 3       -0.12030991 -0.006912407      0.6383398 -0.07768727 -0.06738593
## 1       -0.18590216 -0.124653364      0.6993820 -0.07768727 -0.16068118
## 10       0.10680362  0.184181019      0.2066116 -0.07768727 -0.09085662
```

Our first cluster appears to be overwhelmingly spam, with an overwhelmingly large spam value. Our second cluster has a high dating value, and a somewhat large chatter value, implying it contains users focused around dating. The third cluster has an overwhelming large adult value, implying it is users focused on looking at... "adult" things. Cluster 4 has larg values in tv_film, art, and crafts, implying this is used by users who primarily want to discuss various media they consume and look at cool crafts. The fifth cluster appears to be college students, talking mostly about college and tv_film.The sixth is again similar, again college student users, but ones who care more about music. Both clusters 5 and 6 care some about business, perhaps because they are college students looking for jobs.

The other clusters are not discussed for the purpose of brevity, although they would also be shown in a broader analysis.

The Reuters corpus

Our goal is to predict author of article based upon the article itself. We believe this to be a useful question, as it could perhaps be used as a tool in detecting anonymously written articles or plagarism.

First, we read in the 50 training articles for each of the 50 different authors. Then set training Corpus.

After reading in the data, we pre-processed the text in the articles. * Converting all text to lowercase * Remove numbers * Remove punctuation * Remove excess white space

```
## <<DocumentTermMatrix (documents: 2500, terms: 33472)>>
## Non-/sparse entries: 628611/83051389
## Sparsity           : 99%
## Maximal term length: 45
## Weighting          : term frequency (tf)
```

```
## <<DocumentTermMatrix (documents: 2500, terms: 33373)>>
## Non-/sparse entries: 545286/82887214
## Sparsity           : 99%
## Maximal term length: 45
## Weighting          : term frequency (tf)
```

```
## <<DocumentTermMatrix (documents: 2500, terms: 3448)>>
## Non-/sparse entries: 428509/8191491
## Sparsity           : 95%
## Maximal term length: 43
## Weighting          : term frequency (tf)
```

After these four steps, we're down to **2500 documents** with **32,669 terms.** * Remove stop and filler words, based on the "basic English" stop words

After removing filler words, we're down to **32,570 terms.** * Removed words that have count 0 in $> 99\%$ of documents

Thus cuts the long tail significantly to only **3393 terms.** * Finally, we converted the raw counts of words in each document to TF-IDF weights.

Then, we replicated the same process to read in the 50 testing articles for the authors. There are 3448 terms in the testing data, compared to only 3393 terms in the training data. We will deal with this in the later procedure.

For the testing data, we did the same pre-processing steps as the training data.

```
## <<DocumentTermMatrix (documents: 2500, terms: 33472)>>
## Non-/sparse entries: 628611/83051389
## Sparsity           : 99%
## Maximal term length: 45
## Weighting          : term frequency (tf)
```

```
## <<DocumentTermMatrix (documents: 2500, terms: 33373)>>
## Non-/sparse entries: 545286/82887214
## Sparsity           : 99%
## Maximal term length: 45
## Weighting          : term frequency (tf)
```

```
## <<DocumentTermMatrix (documents: 2500, terms: 3448)>>
## Non-/sparse entries: 428509/8191491
## Sparsity           : 95%
## Maximal term length: 43
## Weighting          : term frequency (tf)
```

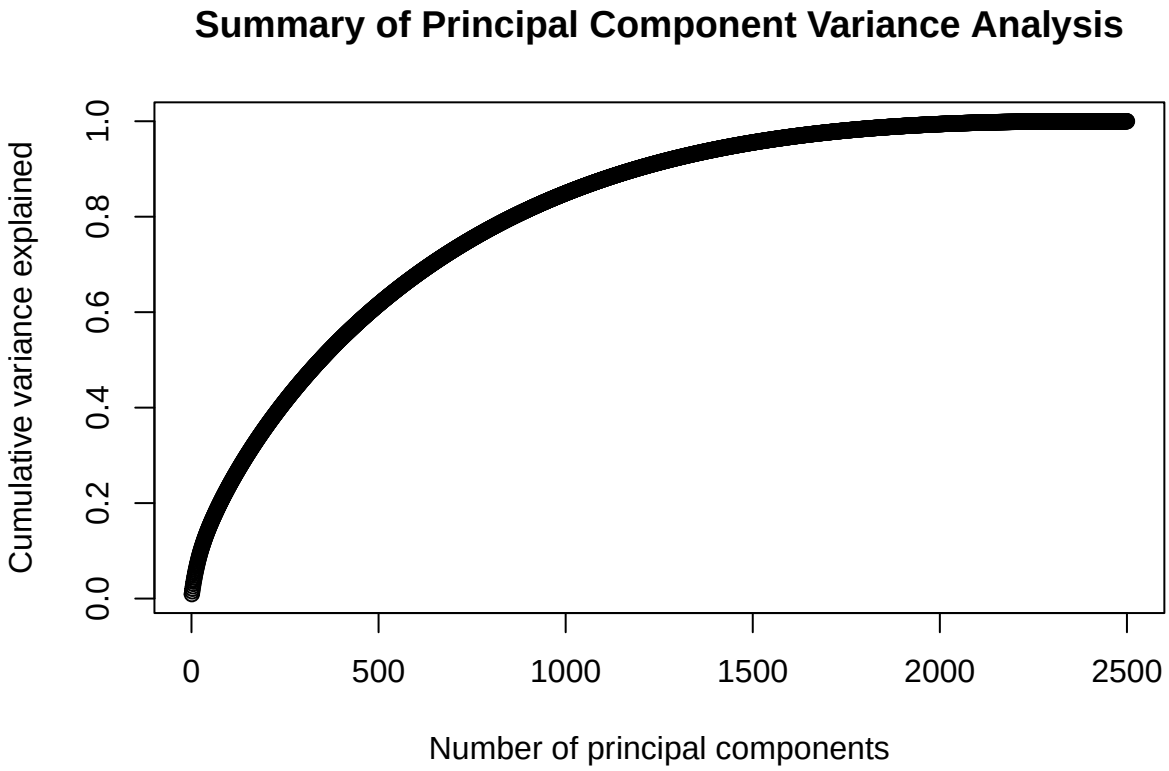
We ignored words that are in the testing set and but not in the training set as below

```
## <<DocumentTermMatrix (documents: 2500, terms: 3448)>>
## Non-/sparse entries: 388509/8231491
## Sparsity           : 95%
## Maximal term length: 43
## Weighting          : term frequency - inverse document frequency (normalized) (tf-idf)
```

This removes the 55 "new" terms from the training data, less than 2% of the training terms. After this procedure, both of the training and testing groups have 3393 terms.

We now use PCA to simplify the predictors. * We remove columns that have zero entries. * We use only intersecting columns of the train and testing data.

PCA process:



We stop at 1000 principal components because it already can explain 80% of the variance as shown in the chart above.

We now can move on to the models. We chose to Naive Bayes and Random Forest to do so.

Random Forest

The random forest model with mtry = $=\sqrt(n_{features}) \approx 50$

```
## [1] 0.8316
```

The Random Forest accuracy is 83.16%.

Naive Bayes

We then used a Naive Bayes model to predict the testing data from a training data.

```
## [1] 0.9684
```

The Naive Bayes accuracy is 96.8%, outperforming random forest.

In summary, the Naive Bayes recieved the best accuracy of 96.8%, which is remarkably strong.

.

Association rule mining

```
##        Species     variable value
## 1       setosa Sepal.Length   5.1
## 2       setosa Sepal.Length   4.9
## 3       setosa Sepal.Length   4.7
## 4       setosa Sepal.Length   4.6
## 5       setosa Sepal.Length   5.0
## 6       setosa Sepal.Length   5.4
## 7       setosa Sepal.Length   4.6
## 8       setosa Sepal.Length   5.0
## 9       setosa Sepal.Length   4.4
## 10      setosa Sepal.Length   4.9
## 11      setosa Sepal.Length   5.4
## 12      setosa Sepal.Length   4.8
## 13      setosa Sepal.Length   4.8
## 14      setosa Sepal.Length   4.3
## 15      setosa Sepal.Length   5.8
## 16      setosa Sepal.Length   5.7
## 17      setosa Sepal.Length   5.4
## 18      setosa Sepal.Length   5.1
## 19      setosa Sepal.Length   5.7
## 20      setosa Sepal.Length   5.1
## 21      setosa Sepal.Length   5.4
## 22      setosa Sepal.Length   5.1
## 23      setosa Sepal.Length   4.6
## 24      setosa Sepal.Length   5.1
## 25      setosa Sepal.Length   4.8
## 26      setosa Sepal.Length   5.0
## 27      setosa Sepal.Length   5.0
## 28      setosa Sepal.Length   5.2
## 29      setosa Sepal.Length   5.2
## 30      setosa Sepal.Length   4.7
## 31      setosa Sepal.Length   4.8
## 32      setosa Sepal.Length   5.4
## 33      setosa Sepal.Length   5.2
## 34      setosa Sepal.Length   5.5
## 35      setosa Sepal.Length   4.9
## 36      setosa Sepal.Length   5.0
## 37      setosa Sepal.Length   5.5
## 38      setosa Sepal.Length   4.9
## 39      setosa Sepal.Length   4.4
## 40      setosa Sepal.Length   5.1
## 41      setosa Sepal.Length   5.0
## 42      setosa Sepal.Length   4.5
## 43      setosa Sepal.Length   4.4
## 44      setosa Sepal.Length   5.0
## 45      setosa Sepal.Length   5.1
## 46      setosa Sepal.Length   4.8
## 47      setosa Sepal.Length   5.1
## 48      setosa Sepal.Length   4.6
## 49      setosa Sepal.Length   5.3
## 50      setosa Sepal.Length   5.0
## 51  versicolor Sepal.Length   7.0
```

```
## 52  versicolor Sepal.Length   6.4
## 53  versicolor Sepal.Length   6.9
## 54  versicolor Sepal.Length   5.5
## 55  versicolor Sepal.Length   6.5
## 56  versicolor Sepal.Length   5.7
## 57  versicolor Sepal.Length   6.3
## 58  versicolor Sepal.Length   4.9
## 59  versicolor Sepal.Length   6.6
## 60  versicolor Sepal.Length   5.2
## 61  versicolor Sepal.Length   5.0
## 62  versicolor Sepal.Length   5.9
## 63  versicolor Sepal.Length   6.0
## 64  versicolor Sepal.Length   6.1
## 65  versicolor Sepal.Length   5.6
## 66  versicolor Sepal.Length   6.7
## 67  versicolor Sepal.Length   5.6
## 68  versicolor Sepal.Length   5.8
## 69  versicolor Sepal.Length   6.2
## 70  versicolor Sepal.Length   5.6
## 71  versicolor Sepal.Length   5.9
## 72  versicolor Sepal.Length   6.1
## 73  versicolor Sepal.Length   6.3
## 74  versicolor Sepal.Length   6.1
## 75  versicolor Sepal.Length   6.4
## 76  versicolor Sepal.Length   6.6
## 77  versicolor Sepal.Length   6.8
## 78  versicolor Sepal.Length   6.7
## 79  versicolor Sepal.Length   6.0
## 80  versicolor Sepal.Length   5.7
## 81  versicolor Sepal.Length   5.5
## 82  versicolor Sepal.Length   5.5
## 83  versicolor Sepal.Length   5.8
## 84  versicolor Sepal.Length   6.0
## 85  versicolor Sepal.Length   5.4
## 86  versicolor Sepal.Length   6.0
## 87  versicolor Sepal.Length   6.7
## 88  versicolor Sepal.Length   6.3
## 89  versicolor Sepal.Length   5.6
## 90  versicolor Sepal.Length   5.5
## 91  versicolor Sepal.Length   5.5
## 92  versicolor Sepal.Length   6.1
## 93  versicolor Sepal.Length   5.8
## 94  versicolor Sepal.Length   5.0
## 95  versicolor Sepal.Length   5.6
## 96  versicolor Sepal.Length   5.7
## 97  versicolor Sepal.Length   5.7
## 98  versicolor Sepal.Length   6.2
## 99  versicolor Sepal.Length   5.1
## 100 versicolor Sepal.Length   5.7
## 101  virginica Sepal.Length   6.3
## 102  virginica Sepal.Length   5.8
## 103  virginica Sepal.Length   7.1
## 104  virginica Sepal.Length   6.3
## 105  virginica Sepal.Length   6.5
```

```
## 106  virginica Sepal.Length   7.6
## 107  virginica Sepal.Length   4.9
## 108  virginica Sepal.Length   7.3
## 109  virginica Sepal.Length   6.7
## 110  virginica Sepal.Length   7.2
## 111  virginica Sepal.Length   6.5
## 112  virginica Sepal.Length   6.4
## 113  virginica Sepal.Length   6.8
## 114  virginica Sepal.Length   5.7
## 115  virginica Sepal.Length   5.8
## 116  virginica Sepal.Length   6.4
## 117  virginica Sepal.Length   6.5
## 118  virginica Sepal.Length   7.7
## 119  virginica Sepal.Length   7.7
## 120  virginica Sepal.Length   6.0
## 121  virginica Sepal.Length   6.9
## 122  virginica Sepal.Length   5.6
## 123  virginica Sepal.Length   7.7
## 124  virginica Sepal.Length   6.3
## 125  virginica Sepal.Length   6.7
## 126  virginica Sepal.Length   7.2
## 127  virginica Sepal.Length   6.2
## 128  virginica Sepal.Length   6.1
## 129  virginica Sepal.Length   6.4
## 130  virginica Sepal.Length   7.2
## 131  virginica Sepal.Length   7.4
## 132  virginica Sepal.Length   7.9
## 133  virginica Sepal.Length   6.4
## 134  virginica Sepal.Length   6.3
## 135  virginica Sepal.Length   6.1
## 136  virginica Sepal.Length   7.7
## 137  virginica Sepal.Length   6.3
## 138  virginica Sepal.Length   6.4
## 139  virginica Sepal.Length   6.0
## 140  virginica Sepal.Length   6.9
## 141  virginica Sepal.Length   6.7
## 142  virginica Sepal.Length   6.9
## 143  virginica Sepal.Length   5.8
## 144  virginica Sepal.Length   6.8
## 145  virginica Sepal.Length   6.7
## 146  virginica Sepal.Length   6.7
## 147  virginica Sepal.Length   6.3
## 148  virginica Sepal.Length   6.5
## 149  virginica Sepal.Length   6.2
## 150  virginica Sepal.Length   5.9
## 151     setosa  Sepal.Width   3.5
## 152     setosa  Sepal.Width   3.0
## 153     setosa  Sepal.Width   3.2
## 154     setosa  Sepal.Width   3.1
## 155     setosa  Sepal.Width   3.6
## 156     setosa  Sepal.Width   3.9
## 157     setosa  Sepal.Width   3.4
## 158     setosa  Sepal.Width   3.4
## 159     setosa  Sepal.Width   2.9
```

```
## 160     setosa  Sepal.Width   3.1
## 161     setosa  Sepal.Width   3.7
## 162     setosa  Sepal.Width   3.4
## 163     setosa  Sepal.Width   3.0
## 164     setosa  Sepal.Width   3.0
## 165     setosa  Sepal.Width   4.0
## 166     setosa  Sepal.Width   4.4
## 167     setosa  Sepal.Width   3.9
## 168     setosa  Sepal.Width   3.5
## 169     setosa  Sepal.Width   3.8
## 170     setosa  Sepal.Width   3.8
## 171     setosa  Sepal.Width   3.4
## 172     setosa  Sepal.Width   3.7
## 173     setosa  Sepal.Width   3.6
## 174     setosa  Sepal.Width   3.3
## 175     setosa  Sepal.Width   3.4
## 176     setosa  Sepal.Width   3.0
## 177     setosa  Sepal.Width   3.4
## 178     setosa  Sepal.Width   3.5
## 179     setosa  Sepal.Width   3.4
## 180     setosa  Sepal.Width   3.2
## 181     setosa  Sepal.Width   3.1
## 182     setosa  Sepal.Width   3.4
## 183     setosa  Sepal.Width   4.1
## 184     setosa  Sepal.Width   4.2
## 185     setosa  Sepal.Width   3.1
## 186     setosa  Sepal.Width   3.2
## 187     setosa  Sepal.Width   3.5
## 188     setosa  Sepal.Width   3.6
## 189     setosa  Sepal.Width   3.0
## 190     setosa  Sepal.Width   3.4
## 191     setosa  Sepal.Width   3.5
## 192     setosa  Sepal.Width   2.3
## 193     setosa  Sepal.Width   3.2
## 194     setosa  Sepal.Width   3.5
## 195     setosa  Sepal.Width   3.8
## 196     setosa  Sepal.Width   3.0
## 197     setosa  Sepal.Width   3.8
## 198     setosa  Sepal.Width   3.2
## 199     setosa  Sepal.Width   3.7
## 200     setosa  Sepal.Width   3.3
## 201 versicolor  Sepal.Width   3.2
## 202 versicolor  Sepal.Width   3.2
## 203 versicolor  Sepal.Width   3.1
## 204 versicolor  Sepal.Width   2.3
## 205 versicolor  Sepal.Width   2.8
## 206 versicolor  Sepal.Width   2.8
## 207 versicolor  Sepal.Width   3.3
## 208 versicolor  Sepal.Width   2.4
## 209 versicolor  Sepal.Width   2.9
## 210 versicolor  Sepal.Width   2.7
## 211 versicolor  Sepal.Width   2.0
## 212 versicolor  Sepal.Width   3.0
## 213 versicolor  Sepal.Width   2.2
```

```
## 214 versicolor  Sepal.Width   2.9
## 215 versicolor  Sepal.Width   2.9
## 216 versicolor  Sepal.Width   3.1
## 217 versicolor  Sepal.Width   3.0
## 218 versicolor  Sepal.Width   2.7
## 219 versicolor  Sepal.Width   2.2
## 220 versicolor  Sepal.Width   2.5
## 221 versicolor  Sepal.Width   3.2
## 222 versicolor  Sepal.Width   2.8
## 223 versicolor  Sepal.Width   2.5
## 224 versicolor  Sepal.Width   2.8
## 225 versicolor  Sepal.Width   2.9
## 226 versicolor  Sepal.Width   3.0
## 227 versicolor  Sepal.Width   2.8
## 228 versicolor  Sepal.Width   3.0
## 229 versicolor  Sepal.Width   2.9
## 230 versicolor  Sepal.Width   2.6
## 231 versicolor  Sepal.Width   2.4
## 232 versicolor  Sepal.Width   2.4
## 233 versicolor  Sepal.Width   2.7
## 234 versicolor  Sepal.Width   2.7
## 235 versicolor  Sepal.Width   3.0
## 236 versicolor  Sepal.Width   3.4
## 237 versicolor  Sepal.Width   3.1
## 238 versicolor  Sepal.Width   2.3
## 239 versicolor  Sepal.Width   3.0
## 240 versicolor  Sepal.Width   2.5
## 241 versicolor  Sepal.Width   2.6
## 242 versicolor  Sepal.Width   3.0
## 243 versicolor  Sepal.Width   2.6
## 244 versicolor  Sepal.Width   2.3
## 245 versicolor  Sepal.Width   2.7
## 246 versicolor  Sepal.Width   3.0
## 247 versicolor  Sepal.Width   2.9
## 248 versicolor  Sepal.Width   2.9
## 249 versicolor  Sepal.Width   2.5
## 250 versicolor  Sepal.Width   2.8
## 251  virginica  Sepal.Width   3.3
## 252  virginica  Sepal.Width   2.7
## 253  virginica  Sepal.Width   3.0
## 254  virginica  Sepal.Width   2.9
## 255  virginica  Sepal.Width   3.0
## 256  virginica  Sepal.Width   3.0
## 257  virginica  Sepal.Width   2.5
## 258  virginica  Sepal.Width   2.9
## 259  virginica  Sepal.Width   2.5
## 260  virginica  Sepal.Width   3.6
## 261  virginica  Sepal.Width   3.2
## 262  virginica  Sepal.Width   2.7
## 263  virginica  Sepal.Width   3.0
## 264  virginica  Sepal.Width   2.5
## 265  virginica  Sepal.Width   2.8
## 266  virginica  Sepal.Width   3.2
## 267  virginica  Sepal.Width   3.0
```

```
## 268  virginica  Sepal.Width   3.8
## 269  virginica  Sepal.Width   2.6
## 270  virginica  Sepal.Width   2.2
## 271  virginica  Sepal.Width   3.2
## 272  virginica  Sepal.Width   2.8
## 273  virginica  Sepal.Width   2.8
## 274  virginica  Sepal.Width   2.7
## 275  virginica  Sepal.Width   3.3
## 276  virginica  Sepal.Width   3.2
## 277  virginica  Sepal.Width   2.8
## 278  virginica  Sepal.Width   3.0
## 279  virginica  Sepal.Width   2.8
## 280  virginica  Sepal.Width   3.0
## 281  virginica  Sepal.Width   2.8
## 282  virginica  Sepal.Width   3.8
## 283  virginica  Sepal.Width   2.8
## 284  virginica  Sepal.Width   2.8
## 285  virginica  Sepal.Width   2.6
## 286  virginica  Sepal.Width   3.0
## 287  virginica  Sepal.Width   3.4
## 288  virginica  Sepal.Width   3.1
## 289  virginica  Sepal.Width   3.0
## 290  virginica  Sepal.Width   3.1
## 291  virginica  Sepal.Width   3.1
## 292  virginica  Sepal.Width   3.1
## 293  virginica  Sepal.Width   2.7
## 294  virginica  Sepal.Width   3.2
## 295  virginica  Sepal.Width   3.3
## 296  virginica  Sepal.Width   3.0
## 297  virginica  Sepal.Width   2.5
## 298  virginica  Sepal.Width   3.0
## 299  virginica  Sepal.Width   3.4
## 300  virginica  Sepal.Width   3.0
## 301     setosa Petal.Length   1.4
## 302     setosa Petal.Length   1.4
## 303     setosa Petal.Length   1.3
## 304     setosa Petal.Length   1.5
## 305     setosa Petal.Length   1.4
## 306     setosa Petal.Length   1.7
## 307     setosa Petal.Length   1.4
## 308     setosa Petal.Length   1.5
## 309     setosa Petal.Length   1.4
## 310     setosa Petal.Length   1.5
## 311     setosa Petal.Length   1.5
## 312     setosa Petal.Length   1.6
## 313     setosa Petal.Length   1.4
## 314     setosa Petal.Length   1.1
## 315     setosa Petal.Length   1.2
## 316     setosa Petal.Length   1.5
## 317     setosa Petal.Length   1.3
## 318     setosa Petal.Length   1.4
## 319     setosa Petal.Length   1.7
## 320     setosa Petal.Length   1.5
## 321     setosa Petal.Length   1.7
```

```
## 322     setosa Petal.Length   1.5
## 323     setosa Petal.Length   1.0
## 324     setosa Petal.Length   1.7
## 325     setosa Petal.Length   1.9
## 326     setosa Petal.Length   1.6
## 327     setosa Petal.Length   1.6
## 328     setosa Petal.Length   1.5
## 329     setosa Petal.Length   1.4
## 330     setosa Petal.Length   1.6
## 331     setosa Petal.Length   1.6
## 332     setosa Petal.Length   1.5
## 333     setosa Petal.Length   1.5
## 334     setosa Petal.Length   1.4
## 335     setosa Petal.Length   1.5
## 336     setosa Petal.Length   1.2
## 337     setosa Petal.Length   1.3
## 338     setosa Petal.Length   1.4
## 339     setosa Petal.Length   1.3
## 340     setosa Petal.Length   1.5
## 341     setosa Petal.Length   1.3
## 342     setosa Petal.Length   1.3
## 343     setosa Petal.Length   1.3
## 344     setosa Petal.Length   1.6
## 345     setosa Petal.Length   1.9
## 346     setosa Petal.Length   1.4
## 347     setosa Petal.Length   1.6
## 348     setosa Petal.Length   1.4
## 349     setosa Petal.Length   1.5
## 350     setosa Petal.Length   1.4
## 351 versicolor Petal.Length   4.7
## 352 versicolor Petal.Length   4.5
## 353 versicolor Petal.Length   4.9
## 354 versicolor Petal.Length   4.0
## 355 versicolor Petal.Length   4.6
## 356 versicolor Petal.Length   4.5
## 357 versicolor Petal.Length   4.7
## 358 versicolor Petal.Length   3.3
## 359 versicolor Petal.Length   4.6
## 360 versicolor Petal.Length   3.9
## 361 versicolor Petal.Length   3.5
## 362 versicolor Petal.Length   4.2
## 363 versicolor Petal.Length   4.0
## 364 versicolor Petal.Length   4.7
## 365 versicolor Petal.Length   3.6
## 366 versicolor Petal.Length   4.4
## 367 versicolor Petal.Length   4.5
## 368 versicolor Petal.Length   4.1
## 369 versicolor Petal.Length   4.5
## 370 versicolor Petal.Length   3.9
## 371 versicolor Petal.Length   4.8
## 372 versicolor Petal.Length   4.0
## 373 versicolor Petal.Length   4.9
## 374 versicolor Petal.Length   4.7
## 375 versicolor Petal.Length   4.3
```

```
## 376 versicolor Petal.Length   4.4
## 377 versicolor Petal.Length   4.8
## 378 versicolor Petal.Length   5.0
## 379 versicolor Petal.Length   4.5
## 380 versicolor Petal.Length   3.5
## 381 versicolor Petal.Length   3.8
## 382 versicolor Petal.Length   3.7
## 383 versicolor Petal.Length   3.9
## 384 versicolor Petal.Length   5.1
## 385 versicolor Petal.Length   4.5
## 386 versicolor Petal.Length   4.5
## 387 versicolor Petal.Length   4.7
## 388 versicolor Petal.Length   4.4
## 389 versicolor Petal.Length   4.1
## 390 versicolor Petal.Length   4.0
## 391 versicolor Petal.Length   4.4
## 392 versicolor Petal.Length   4.6
## 393 versicolor Petal.Length   4.0
## 394 versicolor Petal.Length   3.3
## 395 versicolor Petal.Length   4.2
## 396 versicolor Petal.Length   4.2
## 397 versicolor Petal.Length   4.2
## 398 versicolor Petal.Length   4.3
## 399 versicolor Petal.Length   3.0
## 400 versicolor Petal.Length   4.1
## 401  virginica Petal.Length   6.0
## 402  virginica Petal.Length   5.1
## 403  virginica Petal.Length   5.9
## 404  virginica Petal.Length   5.6
## 405  virginica Petal.Length   5.8
## 406  virginica Petal.Length   6.6
## 407  virginica Petal.Length   4.5
## 408  virginica Petal.Length   6.3
## 409  virginica Petal.Length   5.8
## 410  virginica Petal.Length   6.1
## 411  virginica Petal.Length   5.1
## 412  virginica Petal.Length   5.3
## 413  virginica Petal.Length   5.5
## 414  virginica Petal.Length   5.0
## 415  virginica Petal.Length   5.1
## 416  virginica Petal.Length   5.3
## 417  virginica Petal.Length   5.5
## 418  virginica Petal.Length   6.7
## 419  virginica Petal.Length   6.9
## 420  virginica Petal.Length   5.0
## 421  virginica Petal.Length   5.7
## 422  virginica Petal.Length   4.9
## 423  virginica Petal.Length   6.7
## 424  virginica Petal.Length   4.9
## 425  virginica Petal.Length   5.7
## 426  virginica Petal.Length   6.0
## 427  virginica Petal.Length   4.8
## 428  virginica Petal.Length   4.9
## 429  virginica Petal.Length   5.6
```

```
## 430  virginica Petal.Length   5.8
## 431  virginica Petal.Length   6.1
## 432  virginica Petal.Length   6.4
## 433  virginica Petal.Length   5.6
## 434  virginica Petal.Length   5.1
## 435  virginica Petal.Length   5.6
## 436  virginica Petal.Length   6.1
## 437  virginica Petal.Length   5.6
## 438  virginica Petal.Length   5.5
## 439  virginica Petal.Length   4.8
## 440  virginica Petal.Length   5.4
## 441  virginica Petal.Length   5.6
## 442  virginica Petal.Length   5.1
## 443  virginica Petal.Length   5.1
## 444  virginica Petal.Length   5.9
## 445  virginica Petal.Length   5.7
## 446  virginica Petal.Length   5.2
## 447  virginica Petal.Length   5.0
## 448  virginica Petal.Length   5.2
## 449  virginica Petal.Length   5.4
## 450  virginica Petal.Length   5.1
## 451     setosa  Petal.Width   0.2
## 452     setosa  Petal.Width   0.2
## 453     setosa  Petal.Width   0.2
## 454     setosa  Petal.Width   0.2
## 455     setosa  Petal.Width   0.2
## 456     setosa  Petal.Width   0.4
## 457     setosa  Petal.Width   0.3
## 458     setosa  Petal.Width   0.2
## 459     setosa  Petal.Width   0.2
## 460     setosa  Petal.Width   0.1
## 461     setosa  Petal.Width   0.2
## 462     setosa  Petal.Width   0.2
## 463     setosa  Petal.Width   0.1
## 464     setosa  Petal.Width   0.1
## 465     setosa  Petal.Width   0.2
## 466     setosa  Petal.Width   0.4
## 467     setosa  Petal.Width   0.4
## 468     setosa  Petal.Width   0.3
## 469     setosa  Petal.Width   0.3
## 470     setosa  Petal.Width   0.3
## 471     setosa  Petal.Width   0.2
## 472     setosa  Petal.Width   0.4
## 473     setosa  Petal.Width   0.2
## 474     setosa  Petal.Width   0.5
## 475     setosa  Petal.Width   0.2
## 476     setosa  Petal.Width   0.2
## 477     setosa  Petal.Width   0.4
## 478     setosa  Petal.Width   0.2
## 479     setosa  Petal.Width   0.2
## 480     setosa  Petal.Width   0.2
## 481     setosa  Petal.Width   0.2
## 482     setosa  Petal.Width   0.4
## 483     setosa  Petal.Width   0.1
```

```
## 484     setosa  Petal.Width   0.2
## 485     setosa  Petal.Width   0.2
## 486     setosa  Petal.Width   0.2
## 487     setosa  Petal.Width   0.2
## 488     setosa  Petal.Width   0.1
## 489     setosa  Petal.Width   0.2
## 490     setosa  Petal.Width   0.2
## 491     setosa  Petal.Width   0.3
## 492     setosa  Petal.Width   0.3
## 493     setosa  Petal.Width   0.2
## 494     setosa  Petal.Width   0.6
## 495     setosa  Petal.Width   0.4
## 496     setosa  Petal.Width   0.3
## 497     setosa  Petal.Width   0.2
## 498     setosa  Petal.Width   0.2
## 499     setosa  Petal.Width   0.2
## 500     setosa  Petal.Width   0.2
## 501 versicolor  Petal.Width   1.4
## 502 versicolor  Petal.Width   1.5
## 503 versicolor  Petal.Width   1.5
## 504 versicolor  Petal.Width   1.3
## 505 versicolor  Petal.Width   1.5
## 506 versicolor  Petal.Width   1.3
## 507 versicolor  Petal.Width   1.6
## 508 versicolor  Petal.Width   1.0
## 509 versicolor  Petal.Width   1.3
## 510 versicolor  Petal.Width   1.4
## 511 versicolor  Petal.Width   1.0
## 512 versicolor  Petal.Width   1.5
## 513 versicolor  Petal.Width   1.0
## 514 versicolor  Petal.Width   1.4
## 515 versicolor  Petal.Width   1.3
## 516 versicolor  Petal.Width   1.4
## 517 versicolor  Petal.Width   1.5
## 518 versicolor  Petal.Width   1.0
## 519 versicolor  Petal.Width   1.5
## 520 versicolor  Petal.Width   1.1
## 521 versicolor  Petal.Width   1.8
## 522 versicolor  Petal.Width   1.3
## 523 versicolor  Petal.Width   1.5
## 524 versicolor  Petal.Width   1.2
## 525 versicolor  Petal.Width   1.3
## 526 versicolor  Petal.Width   1.4
## 527 versicolor  Petal.Width   1.4
## 528 versicolor  Petal.Width   1.7
## 529 versicolor  Petal.Width   1.5
## 530 versicolor  Petal.Width   1.0
## 531 versicolor  Petal.Width   1.1
## 532 versicolor  Petal.Width   1.0
## 533 versicolor  Petal.Width   1.2
## 534 versicolor  Petal.Width   1.6
## 535 versicolor  Petal.Width   1.5
## 536 versicolor  Petal.Width   1.6
## 537 versicolor  Petal.Width   1.5
```

```
## 538 versicolor  Petal.Width   1.3
## 539 versicolor  Petal.Width   1.3
## 540 versicolor  Petal.Width   1.3
## 541 versicolor  Petal.Width   1.2
## 542 versicolor  Petal.Width   1.4
## 543 versicolor  Petal.Width   1.2
## 544 versicolor  Petal.Width   1.0
## 545 versicolor  Petal.Width   1.3
## 546 versicolor  Petal.Width   1.2
## 547 versicolor  Petal.Width   1.3
## 548 versicolor  Petal.Width   1.3
## 549 versicolor  Petal.Width   1.1
## 550 versicolor  Petal.Width   1.3
## 551  virginica  Petal.Width   2.5
## 552  virginica  Petal.Width   1.9
## 553  virginica  Petal.Width   2.1
## 554  virginica  Petal.Width   1.8
## 555  virginica  Petal.Width   2.2
## 556  virginica  Petal.Width   2.1
## 557  virginica  Petal.Width   1.7
## 558  virginica  Petal.Width   1.8
## 559  virginica  Petal.Width   1.8
## 560  virginica  Petal.Width   2.5
## 561  virginica  Petal.Width   2.0
## 562  virginica  Petal.Width   1.9
## 563  virginica  Petal.Width   2.1
## 564  virginica  Petal.Width   2.0
## 565  virginica  Petal.Width   2.4
## 566  virginica  Petal.Width   2.3
## 567  virginica  Petal.Width   1.8
## 568  virginica  Petal.Width   2.2
## 569  virginica  Petal.Width   2.3
## 570  virginica  Petal.Width   1.5
## 571  virginica  Petal.Width   2.3
## 572  virginica  Petal.Width   2.0
## 573  virginica  Petal.Width   2.0
## 574  virginica  Petal.Width   1.8
## 575  virginica  Petal.Width   2.1
## 576  virginica  Petal.Width   1.8
## 577  virginica  Petal.Width   1.8
## 578  virginica  Petal.Width   1.8
## 579  virginica  Petal.Width   2.1
## 580  virginica  Petal.Width   1.6
## 581  virginica  Petal.Width   1.9
## 582  virginica  Petal.Width   2.0
## 583  virginica  Petal.Width   2.2
## 584  virginica  Petal.Width   1.5
## 585  virginica  Petal.Width   1.4
## 586  virginica  Petal.Width   2.3
## 587  virginica  Petal.Width   2.4
## 588  virginica  Petal.Width   1.8
## 589  virginica  Petal.Width   1.8
## 590  virginica  Petal.Width   2.1
## 591  virginica  Petal.Width   2.4
```

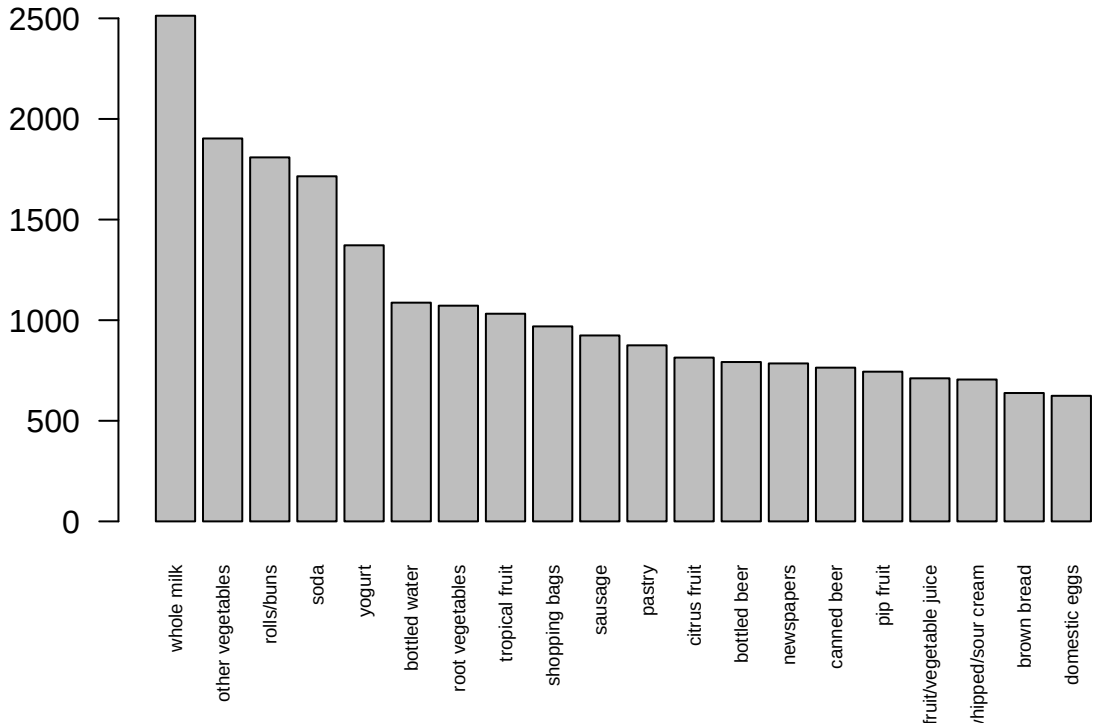
```
## 592  virginica  Petal.Width   2.3
## 593  virginica  Petal.Width   1.9
## 594  virginica  Petal.Width   2.3
## 595  virginica  Petal.Width   2.5
## 596  virginica  Petal.Width   2.3
## 597  virginica  Petal.Width   1.9
## 598  virginica  Petal.Width   2.0
## 599  virginica  Petal.Width   2.3
## 600  virginica  Petal.Width   1.8
```

```
## [[1]]
## [1] "V1" "V2" "V3" "V4"
```

```
## 'data.frame':    43367 obs. of  2 variables:
##  $ User : int  1 1 1 1 2 2 2 3 4 4 ...
##  $ value: chr  "citrus fruit" "semi-finished bread" "margarine" "ready soups" ...
```

```
##       User          value
##  Min.   :    1   Length:43367
##  1st Qu.: 3814   Class :character
##  Median : 7620   Mode  :character
##  Mean   : 7650
##  3rd Qu.:11482
##  Max.   :15296
```

```
##    Length     Class      Mode
##     43367 character character
```

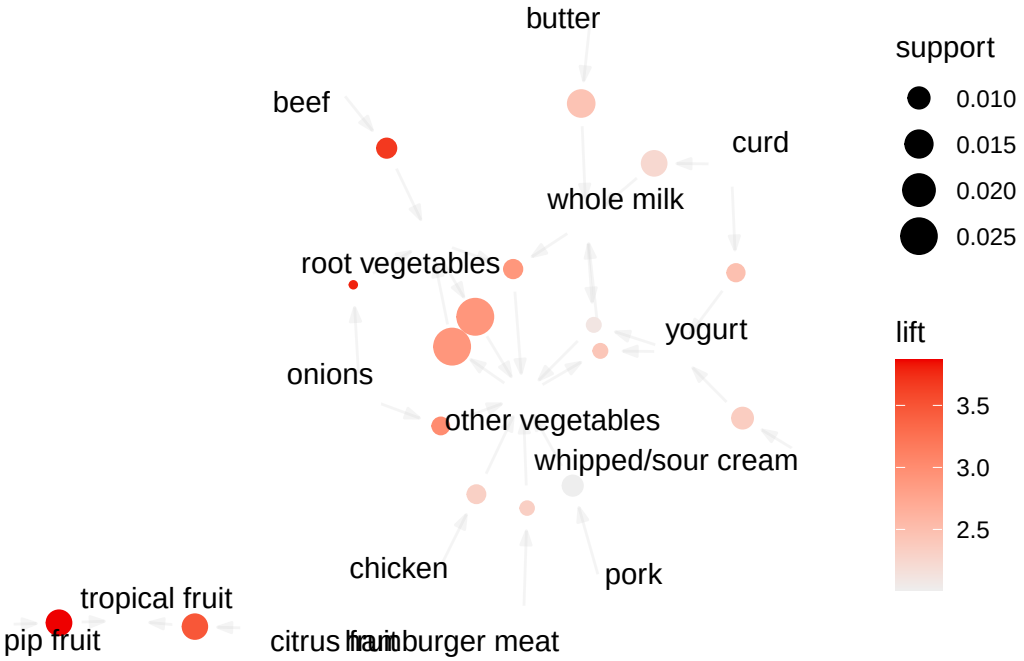


Apriori

```
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5   0.005      1
##  maxlen target  ext
##       4  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 76
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[169 item(s), 15296 transaction(s)] done [0.00s].
## sorting and recoding items ... [101 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 done [0.00s].
## writing ... [118 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
##      lhs                              rhs                support     confidence
## [1]  {onions}                      => {root vegetables}  0.005295502 0.2655738
## [2]  {onions}                      => {other vegetables} 0.007452929 0.3737705
## [3]  {hamburger meat}              => {other vegetables} 0.006210774 0.2905199
## [4]  {chicken}                     => {other vegetables} 0.007975941 0.2890995
## [5]  {beef}                        => {root vegetables}  0.008695084 0.2577519
## [6]  {curd}                        => {yogurt}           0.007649059 0.2232824
## [7]  {curd}                        => {whole milk}       0.012617678 0.3683206
## [8]  {butter}                      => {whole milk}       0.014382845 0.4036697
## [9]  {pork}                        => {other vegetables} 0.009283473 0.2504409
## [10] {whipped/sour cream}          => {yogurt}           0.009741109 0.2113475
## [11] {pip fruit}                   => {tropical fruit}   0.012683054 0.2607527
## [12] {citrus fruit}                => {tropical fruit}   0.012486925 0.2346437
## [13] {root vegetables}             => {other vegetables} 0.025366109 0.3619403
## [14] {other vegetables}            => {root vegetables}  0.025366109 0.2038886
## [15] {root vegetables, whole milk} => {other vegetables} 0.008172071 0.3612717
## [16] {other vegetables, yogurt}    => {whole milk}       0.006341527 0.3991770
## [17] {whole milk, yogurt}          => {other vegetables} 0.006341527 0.2614555
##      coverage   lift     count
## [1]  0.01993985 3.789381  81
## [2]  0.01993985 3.004306 114
## [3]  0.02137814 2.335151  95
## [4]  0.02758891 2.323734 122
## [5]  0.03373431 3.677774 133
## [6]  0.03425732 2.489306 117
## [7]  0.03425732 2.241875 193
## [8]  0.03563023 2.457036 220
## [9]  0.03706851 2.013003 142
## [10] 0.04609048 2.356248 149
## [11] 0.04864017 3.864800 194
## [12] 0.05321653 3.477820 191
## [13] 0.07008368 2.909216 388
## [14] 0.12441161 2.909216 388
```

```
## [15] 0.02262029 2.903842 125
## [16] 0.01588651 2.429690  97
## [17] 0.02425471 2.101536  97
```



As a general heuristic, we chose a lift value of 2. We saw that lower lift values such as 1.5 gave some odd rules, such as onion therefore milk, or curd therefore other vegetables, and higher lift values gave perhaps less rules than one might desire, with 2.5 going down to 18 rules. In general, we also thought that in general doubling the likelihood of buying an item was a good baseline for if an item increased your likelihodo of purchasing. We still saw some odd rules at a lift of 2, such as sausage implies citrus fruit, and believe these to be since we have yet to adjust for confidence. Looking at the data, a confidence threshold of about 0.2 seemed to clean up these issues. It's also a good general value, as if the likelihood of something is less than 20%, we generally consider it very unlikely. We stuck with general round values to prevent overtuning the parameters to get the exact data we wanted. This leaves us with 17 rules.

These rule sets seem to make sense, with types of vegetables, fruit, and dairy implying types of vegetables, fruit and dairy, respectively. It also seems to be picking up on the existence of meals, with chicken, pork, and beef both implying vegetable purchases. Some rules do not entirely make sense, such as whole milk and yogurt implying other vegetables, although this could be picking up on the existence of families, who tend to buy milk and yogurt, but also want healthy children and therefore buy vegetables.