ML Final HW

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Group Members:

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GitHub Link:

https://github.com/meeth414/Intro-to-ML-2-STA-380-Group-Submission

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Probability Practice

Part A

Since the problem states that the expected fraction of random clickers is 0.3, then the fraction of random clickers is a random variable. Thus, the probability of a random clicker is equal to the fraction of random clickers, given that this is a uniform draw. If the fraction of random clickers is a random variable, then the fraction of people who answered yes is also a random variable. We can also say that the expected value of yes is linear because the fraction of truthful clickers and random clickers are random variables. This allows us say that the expected probability of truthful clickers is equal to 1 - 0.3 (the expected probability of random clickers), 0.7. Lastly, the expected probability value of yes is 0.65, because we are certain that the probability of a yes is 65%. Thus, we can solve the expression below, using the rule of total probability, to find the fraction of people who are truthful clickers.

- $E\left[(RandomClicker)\right] = 0.3$
- $P(Yes) = 0.65$
- $P(No) = 0.35$

$E\left[P(Yes)\right] = P(Yes \mid TruthfulClicker) \cdot P(TruthfulClicker) + P(Yes \mid RandomClicker) \cdot E\left[P(RandomClicker)\right]$

$0.65 = (X \cdot\ 0.7) + (0.5 \cdot\ 0.3)$

$X = 71.44\%$ (Or in fraction terms = 0.7144)

Part B

Using the rule of total probability, we were able to conclude that the fraction of people who have the disease, given that they tested positive, was 19.89%.

- $P(Disease \mid Positive) = X$
- $P(Positive \mid Disease) = 0.993$
- $P(Negative \mid NoDisease) = 0.9999$
- $P(Positive \mid NoDisease) = 0.0001$
- $P(Disease) = 0.000025$
- $P(NoDisease) = 0.999975$

$$P(Disease \mid Positive) = \frac{P(Disease) \cdot P(Positive|Disease)}{(P(Disease) \cdot P(Positive|Disease)) + (P(NoDisease) \cdot P(Positive|NoDisease))}$$

$$P(Disease \mid Positive) = \frac{(0.000025 \cdot 0.993)}{(0.000025 \cdot 0.993) + (0.999975 \cdot 0.0001)}$$

$$P(Disease \mid Positive) = 0.198882$$

Wrangling the Billboard Top 100

Part A

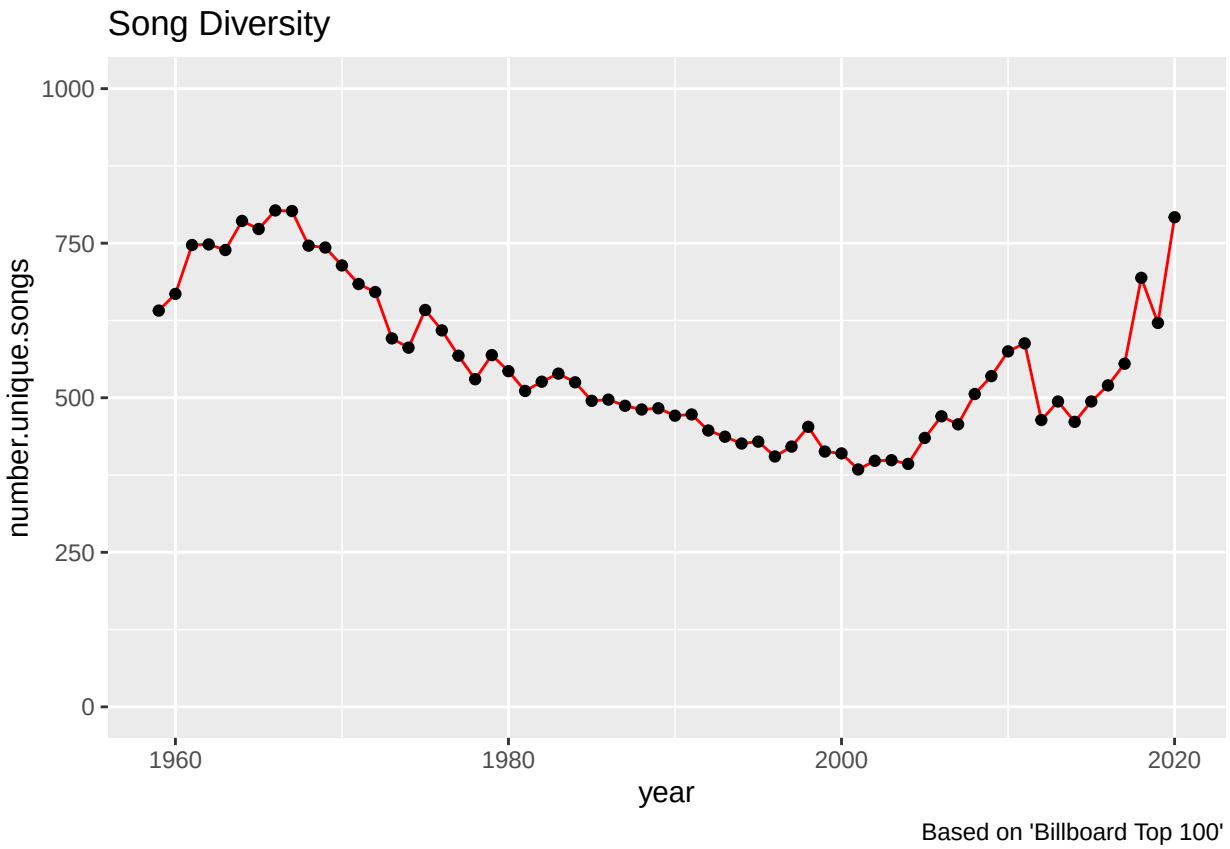
Top 10 most popular songs

```
## # A tibble: 10 x 3
## # Groups:   performer [10]
##    performer                                song                          count
##    <chr>                                    <chr>                         <int>
##  1 Imagine Dragons                          Radioactive                      87
##  2 AWOLNATION                               Sail                             79
##  3 Jason Mraz                               I'm Yours                        76
##  4 LeAnn Rimes                              How Do I Live                    69
##  5 LMFAO Featuring Lauren Bennett & GoonRock Party Rock Anthem               68
##  6 OneRepublic                              Counting Stars                   68
##  7 Adele                                    Rolling In The Deep              65
##  8 Jewel                                    Foolish Games/You Were Meant~    65
##  9 Carrie Underwood                         Before He Cheats                 64
## 10 Lifehouse                                You And Me                       62
```

Comments:
The top 10 most popular songs since 1958 in the 'Billboard Top 100' are: *Radioactive, Sail, I'm Yours, How Do I Live, Party Rock Anthem, Counting Stars, Rolling In The Deep, Foolish Games/You Were Meant For Me, Before He Cheats, You And Me.* The most popular song ever since 1958 has appear in the 'Billboard Top 100' up to 87 weeks.

Part B

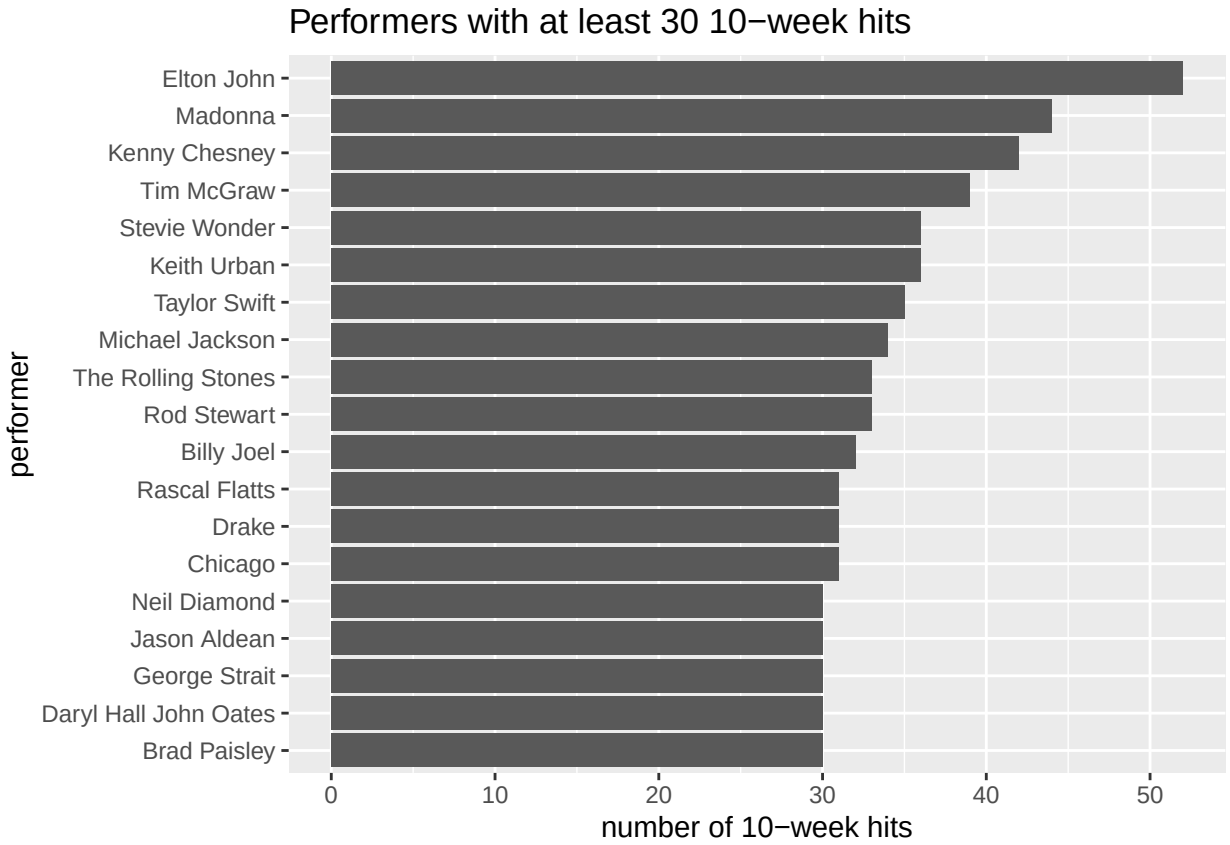
Musical Diversity



Comments:
In this line graph we can observe that the number of different songs which appear in the 'Billboard Top 100' each year had a decreasing trend from 1966 to 2001. Less diversity means that less songs remains much time in year in the 'Billborad Top 10'. On the other hand, this behavior was reverse from 2001 to 2020 in which there was an increasing trend; more diversity.

Part C

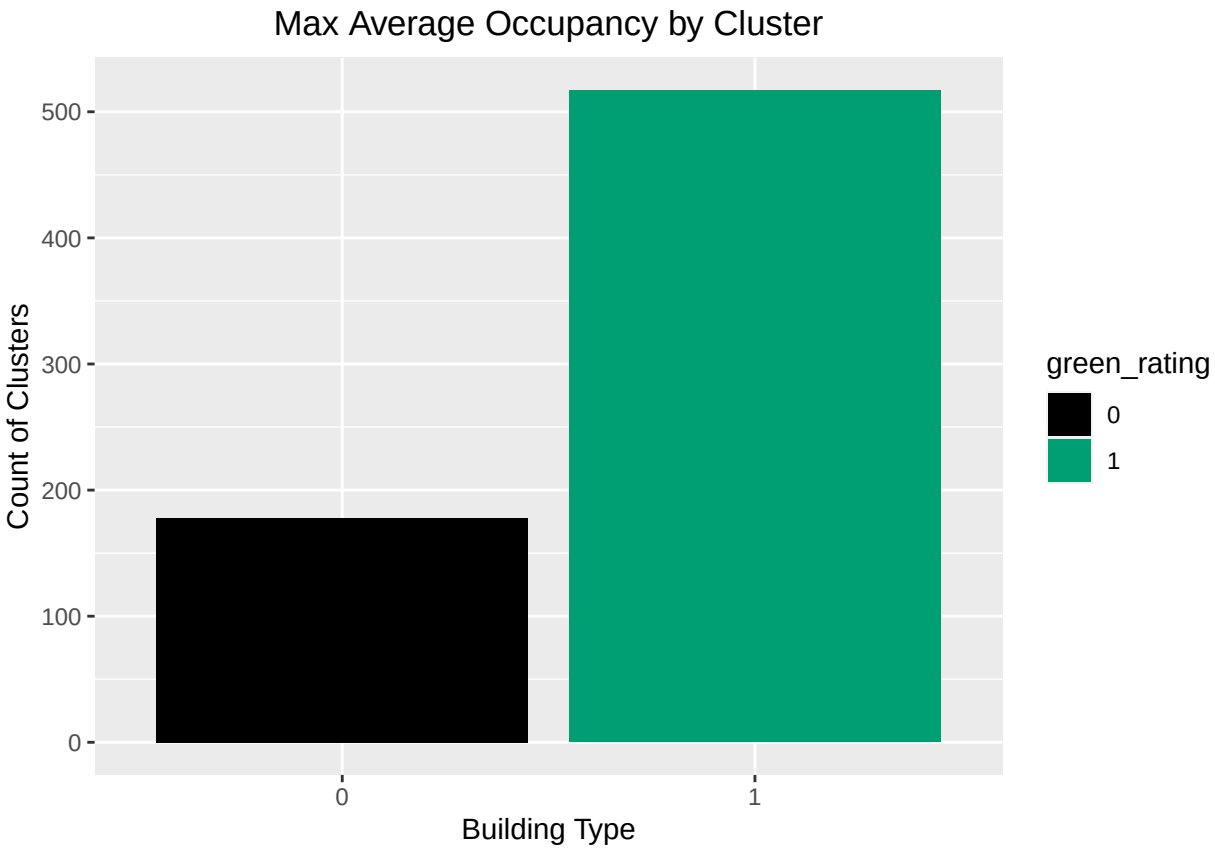
Performers with at least 30 10-week hits

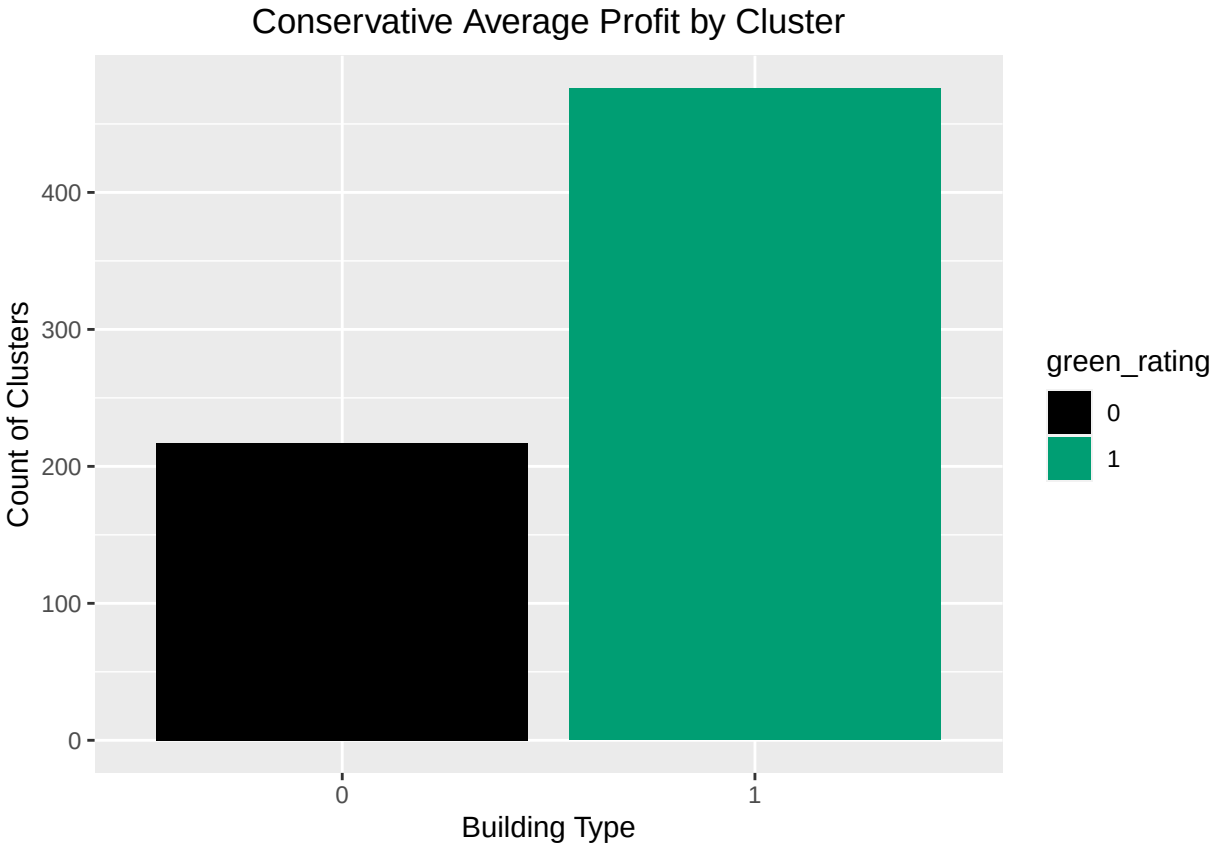


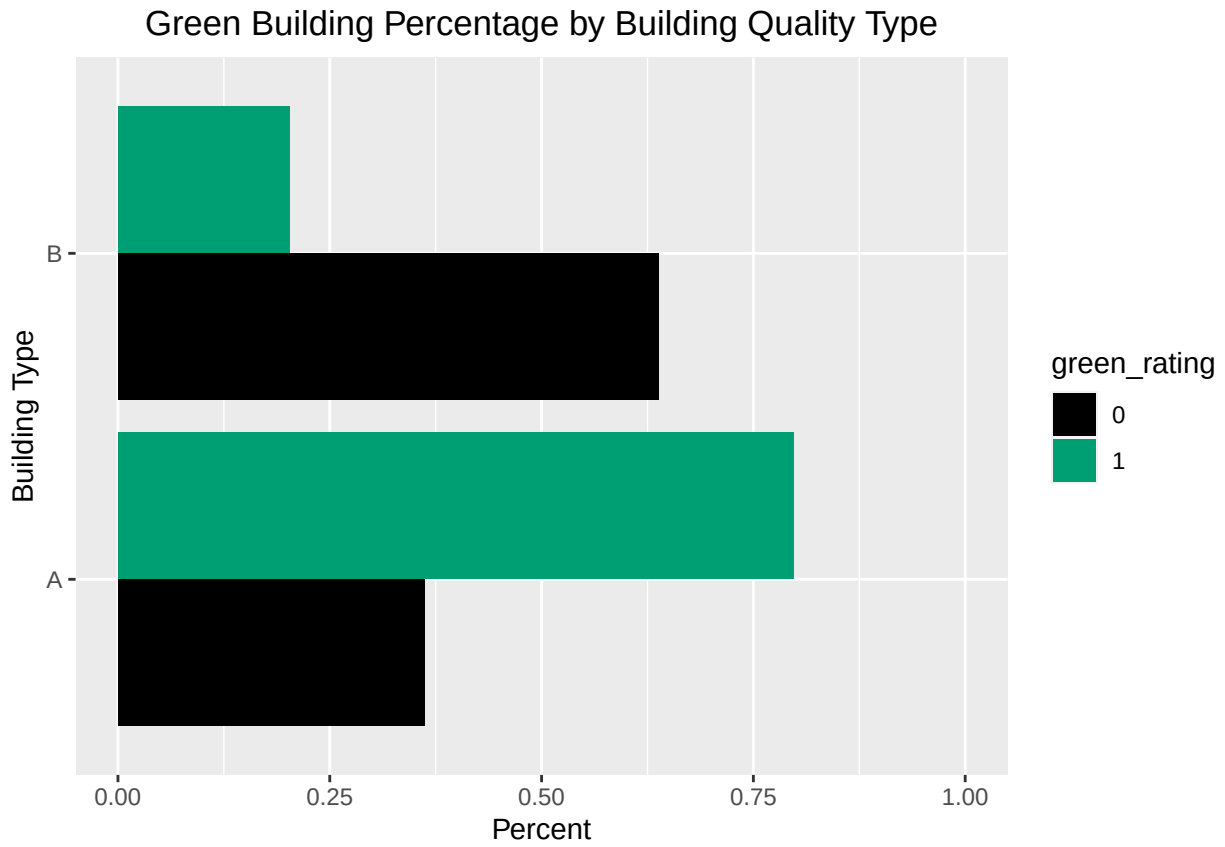
Comments:
This graph show us the 19 artists in U.S. musical history since 1958 who have had at least 30 songs that were "ten-week hits." As we can observe, Elton John is the performer with the more number of that songs (52) and he is followed by Madonna with 44 songs.

Visual story telling part 1: green buildings

```
## # A tibble: 2 x 2
##   green_rating count
##   <fct>        <int>
## 1 0              212
## 2 1              498
```


Max Average Occupancy by Cluster
Count of Clusters
500
400
300
200
100
0
0
1
Building Type
green_rating
0
1


Conservative Average Profit by Cluster
Count of Clusters
400
300
200
100
0
0
1
Building Type
green_rating
0
1



Comments: We agree with the analyst's opinion that a green building would be the best investment for the company. However, we disagree with the analysis to reach that conclusion. In his analysis, he groups all of the houses together without taking into account the different markets across Austin. In addition, since the analysis was based solely off of the expected numbers given, and not accounting for fluctuation, we felt that his analysis was not every strong. Thus, we conducted our own analysis accounting for these variables.

In plot 1, "Max Average Occupancy by Cluster," we can see that the occupancy rates across Austin are primarily in green buildings, allowing us to make the initial conclusion that Austinites tend to prefer green buildings over non-green buildings.

In plot 2, "Conservative Average Profit by Cluster," we accounted for the building types and the average profit by cluster. In order to create this plot, we assumed that all the green buildings paid for the utility costs of the tenant, to get an extremely conservative amount of profit for green buildings vs. non-green buildings. This allows us to conservatively compare the lower-end of profit landlords receive from green buildings compared to non-green buildings. Thus, the profit was calculated as: Rents received - total utility costs. Even with this conservative factor, the average profit by green buildings vastly outperformed the non-green buildings.

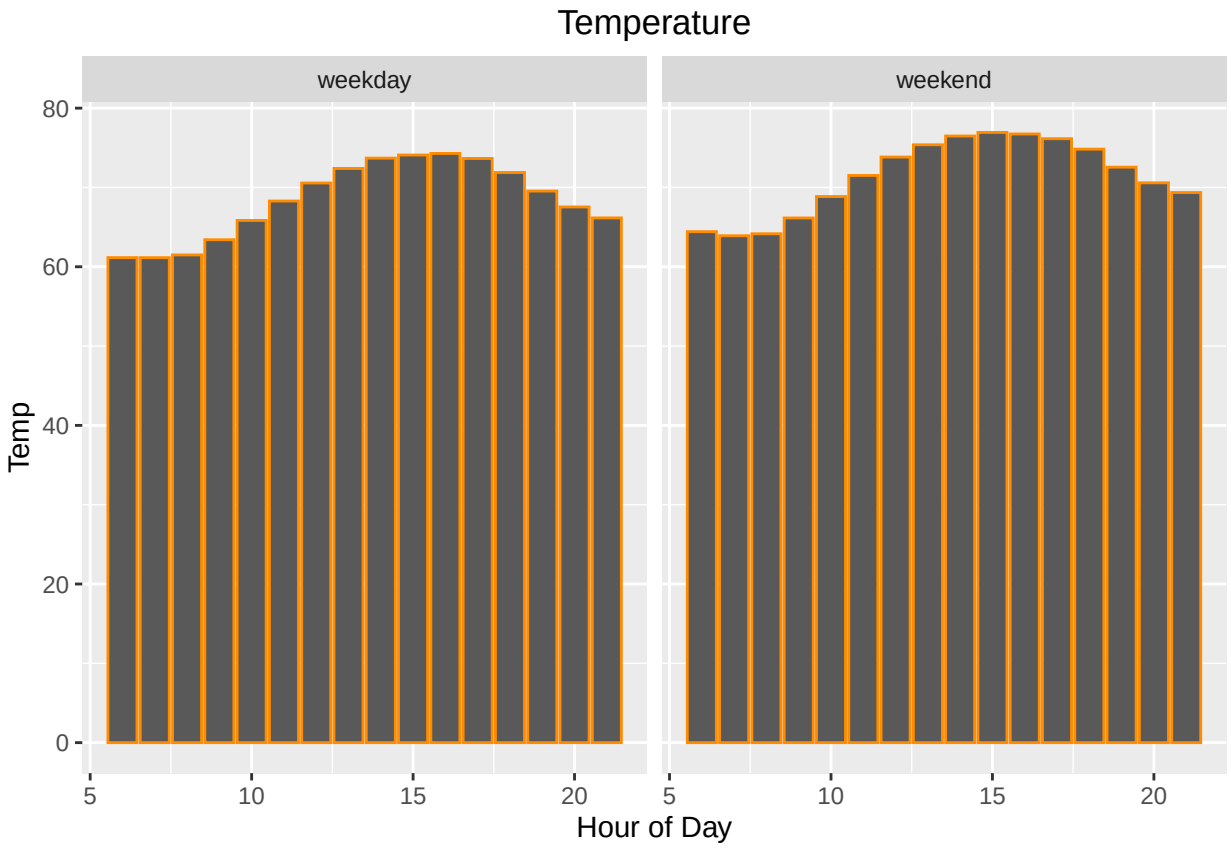
Finally, we wanted to evaluate the building quality, as company brand and longevity is extremely important. In plot 3, "Green Building Percentage by Building Quality Type" we looked at the percentage of green buildings vs. non-green buildings and their respective building quality types. The plot suggests that green buildings have an extremely high ratio of a label of a "good" building quality type compared to the non-green buildings.

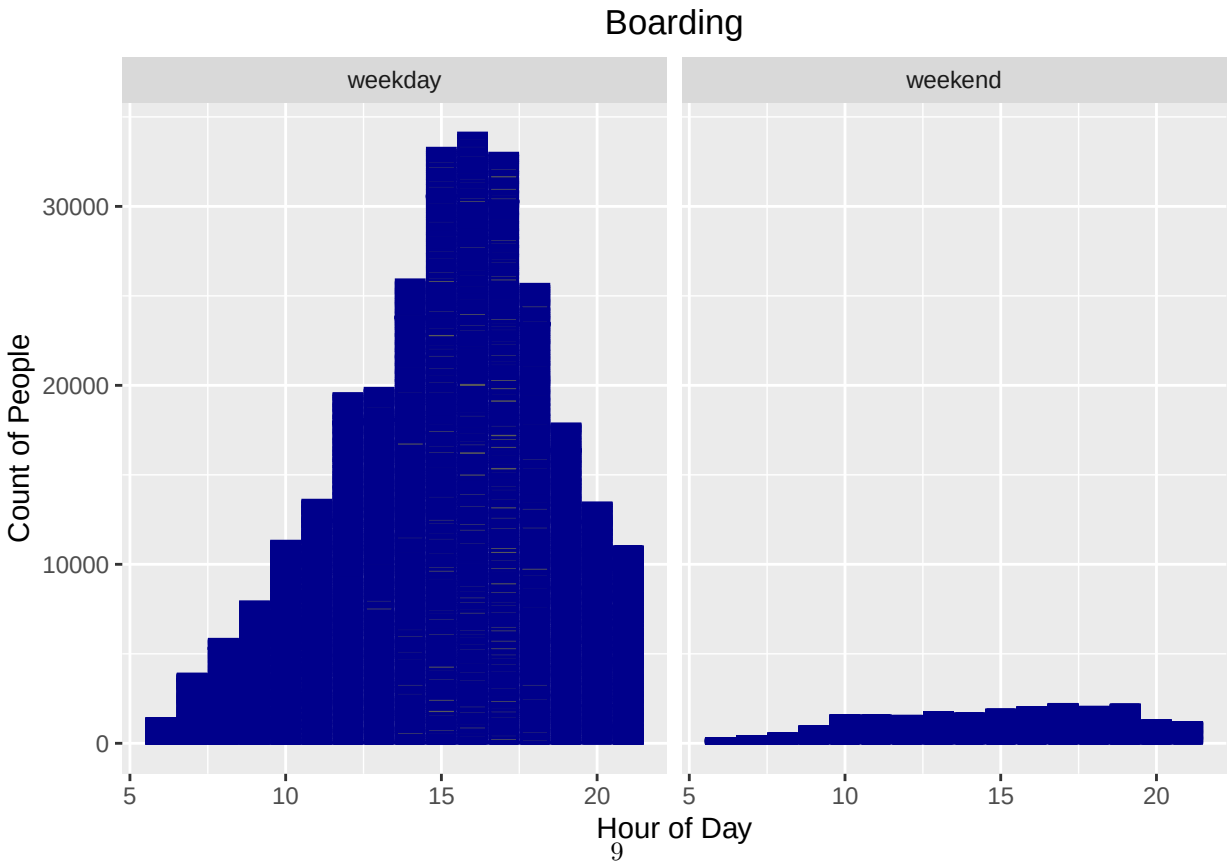
Although we found higher utility costs associated with a few green buildings which was surprising, the average conservative profit generated by each green building cluster was still significantly higher than the non-green buildings.

Thus, we can conclude that the company should invest in a green building, despite the extra initial cost,

since green buildings in this dataset lead to a higher average occupancy, a higher average profit, and a higher building quality rating.

Visual story telling part 2: Capital Metro data





Comments:

The first plot measures the temperature vs. hour of day. We can see that the highest temperatures occur from 3-5P.M. Interestingly, this trend is also seen in the bus boarding rates across each hour, with maximum boarding rates also occurring around 3-5P.M. In order to account for E.O.D. traffic (for after-work commuters), we also looked at the weekend temperatures and the weekend boarding rates. Although not as visually significant as the weekday, this trend still occurs during the weekend.

This allows us to make the conclusion that boarding is seen to have a positive correlation with temperature because as the temperature increases during the day, so does the number of people who want to take the bus. This pattern is probably due to people taking the bus as opposed to walking or taking the car to avoid the extreme heat, as cars can overheat too or be unpleasant to ride in when hot.

Portfolio modeling

```
## [1] "AOK"  "JPST" "GOVT" "VBK"  "SCHG" "DRN"  "SOXX"

## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
## on 'https://query2.finance.yahoo.com/v7/finance/download/AOK?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'

## Warning in read.table(file = file, header = header, sep = sep,
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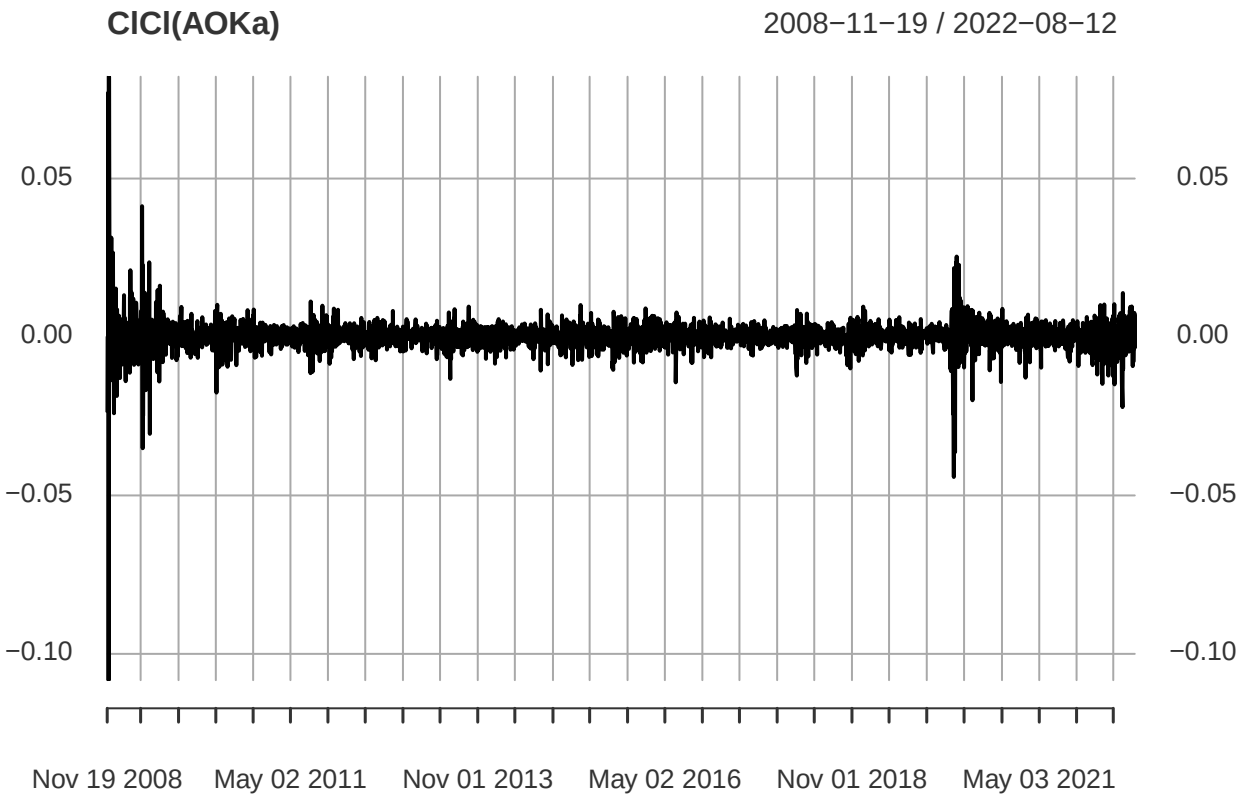
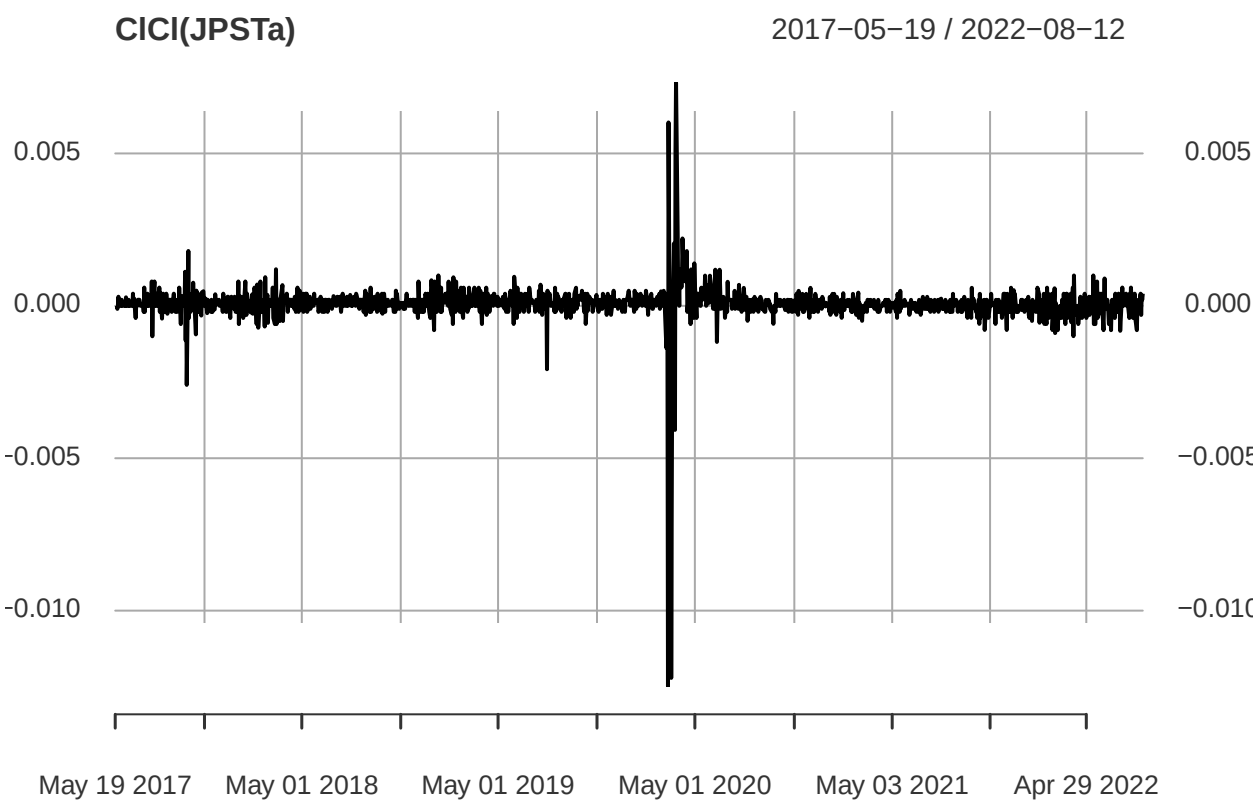
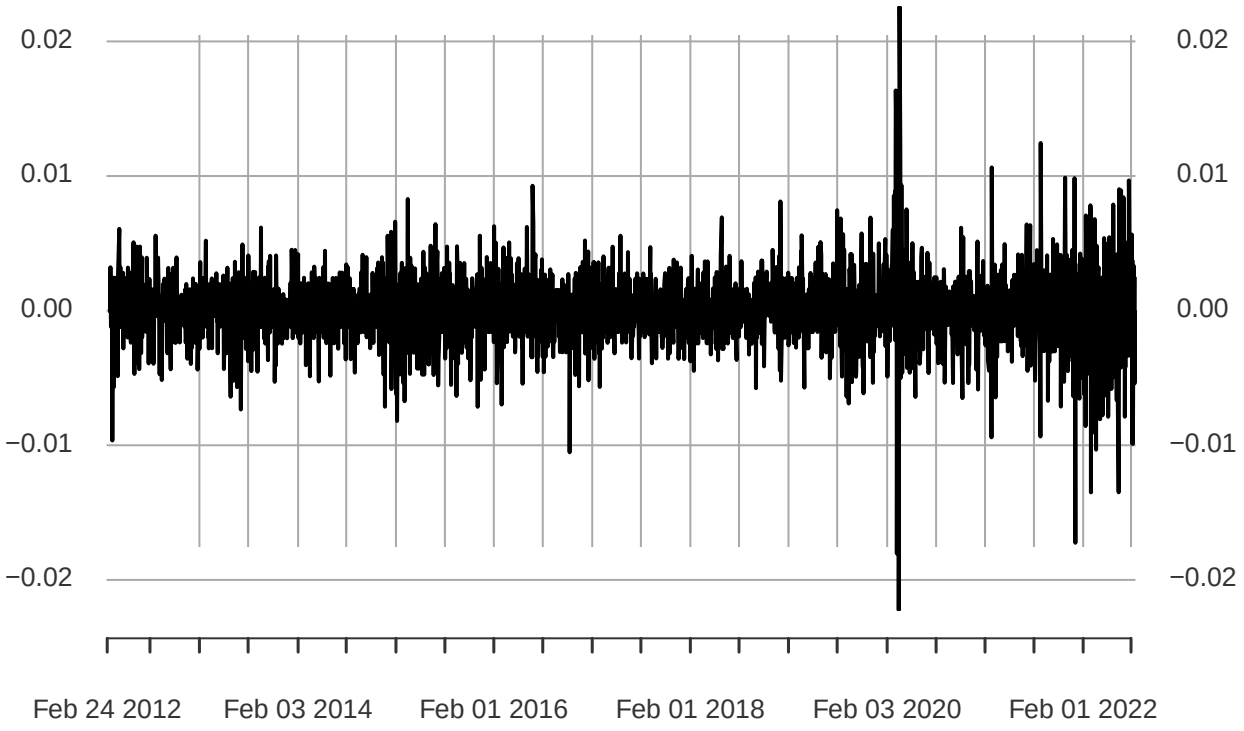
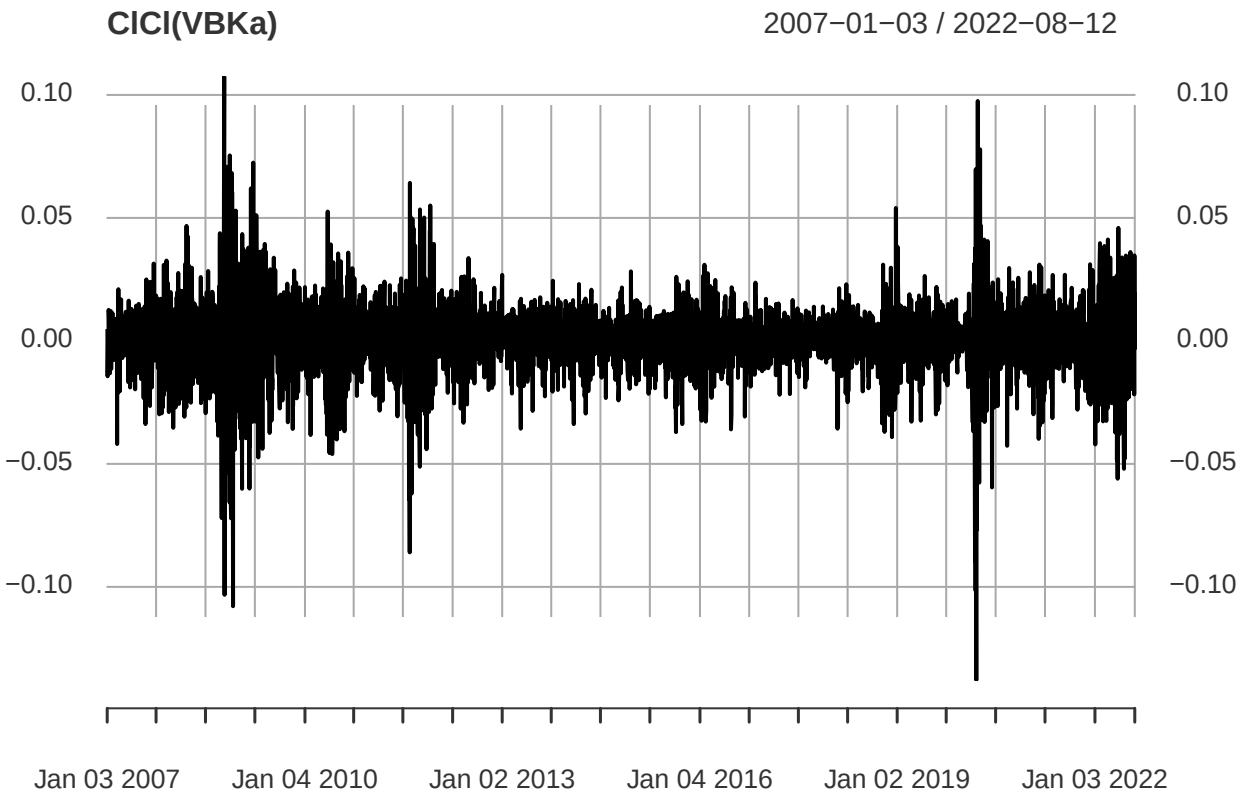
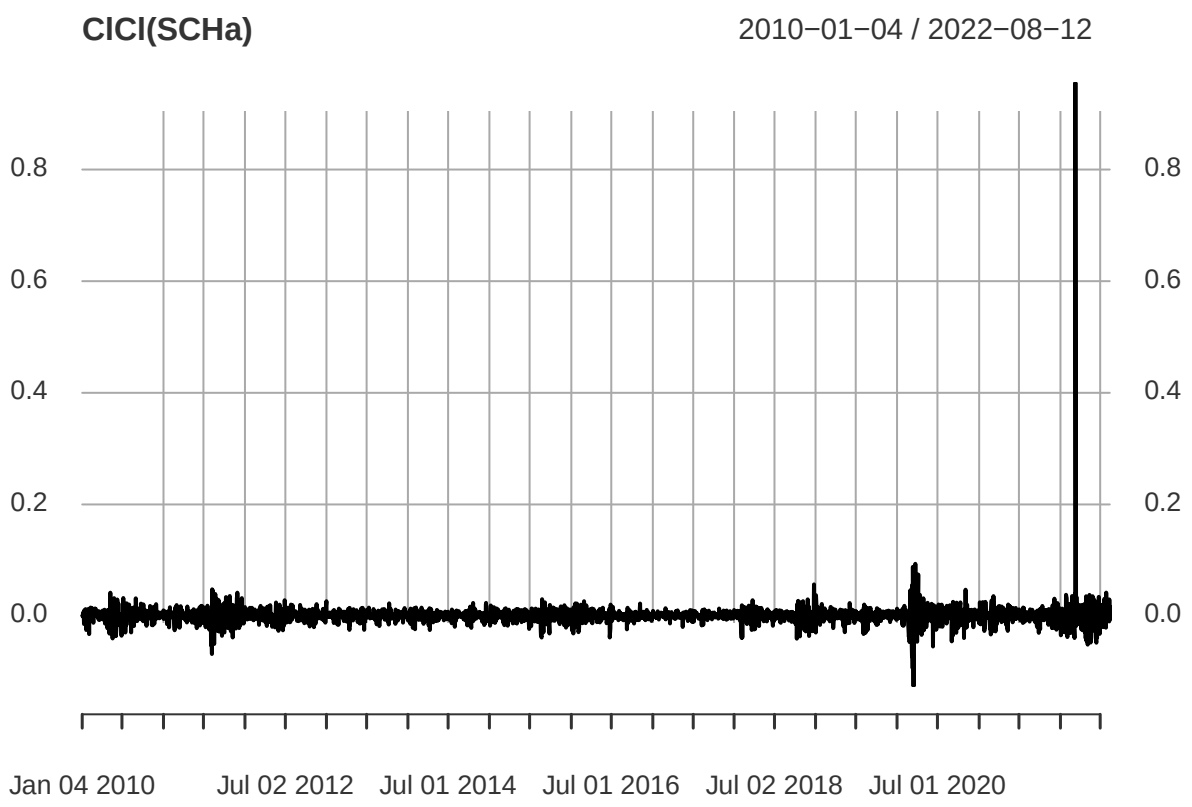
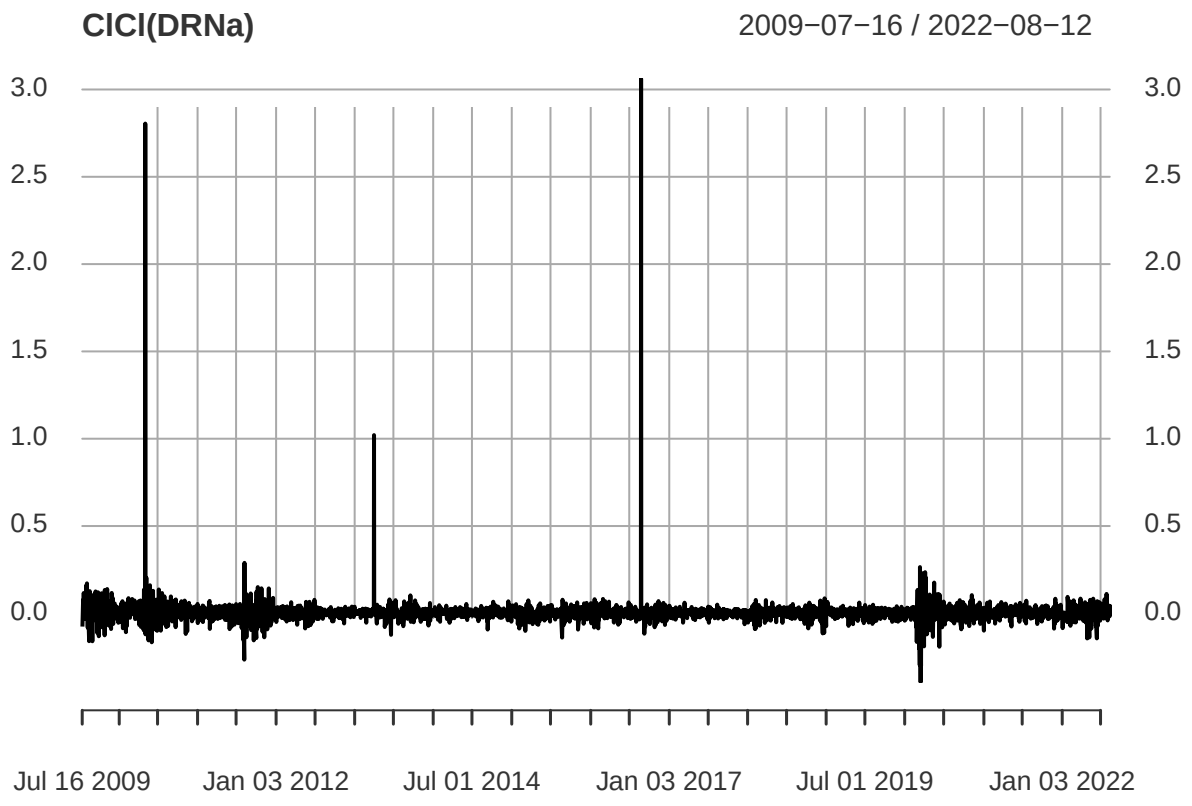

ClCl(AOKa)
2008−11−19 / 2022−08−12
0.05
0.00
−0.05
−0.10
Nov 19 2008
May 02 2011
Nov 01 2013
May 02 2016
Nov 01 2018
May 03 2021

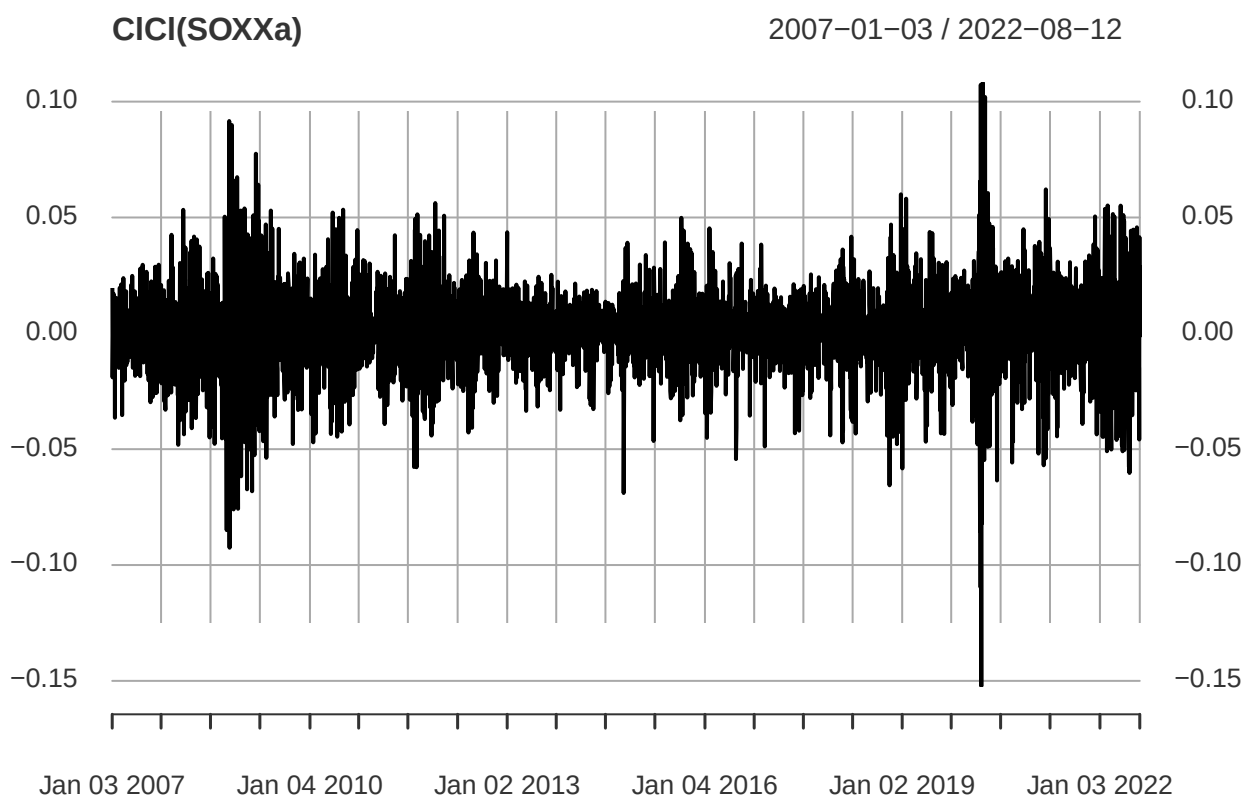

ClCl(JPSTa)
2017−05−19 / 2022−08−12
0.005
0.000
-0.005
-0.010
May 19 2017
May 01 2018
May 01 2019
May 01 2020
May 03 2021
Apr 29 2022


ClCl(GOVTa)
2012−02−24 / 2022−08−12
0.02
0.01
0.00
−0.01
−0.02
Feb 24 2012
Feb 03 2014
Feb 01 2016
Feb 01 2018
Feb 03 2020
Feb 01 2022

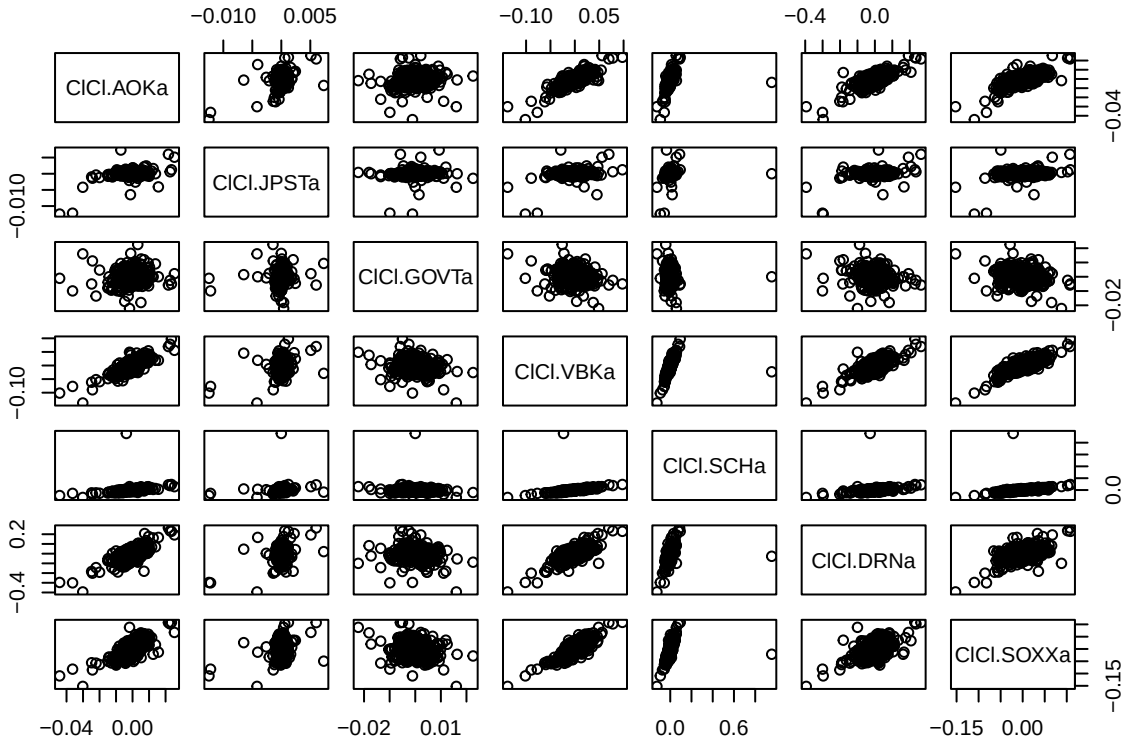

ClCl(VBKa)
2007−01−03 / 2022−08−12
0.10
0.05
0.00
−0.05
−0.10
Jan 03 2007
Jan 04 2010
Jan 02 2013
Jan 04 2016
Jan 02 2019
Jan 03 2022

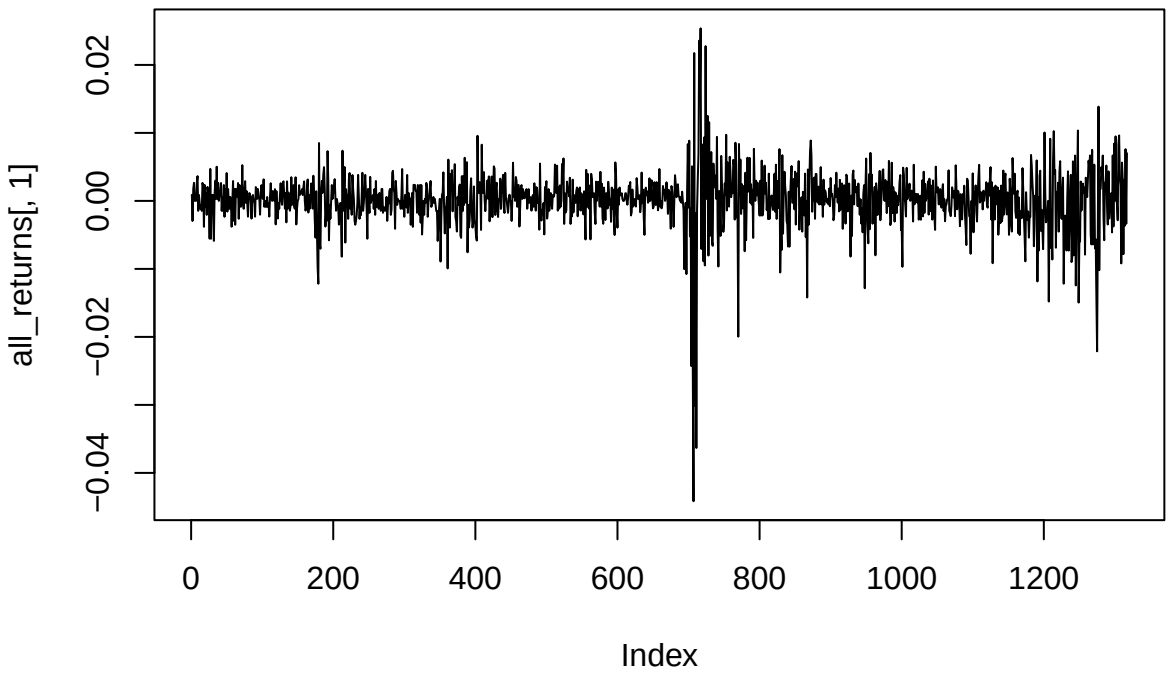

ClCl(SCHa)
2010−01−04 / 2022−08−12
0.8
0.6
0.4
0.2
0.0
Jan 04 2010
Jul 02 2012
Jul 01 2014
Jul 01 2016
Jul 02 2018
Jul 01 2020


ClCl(DRNa)
2009−07−16 / 2022−08−12
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Jul 16 2009
Jan 03 2012
Jul 01 2014
Jan 03 2017
Jul 01 2019
Jan 03 2022




```
##            ClCl.AOKa ClCl.JPSTa ClCl.GOVTa    ClCl.VBKa ClCl.SCHa ClCl.DRNa
## 2007-01-03        NA         NA         NA           NA        NA        NA
## 2007-01-04        NA         NA         NA  0.004758204        NA        NA
## 2007-01-05        NA         NA         NA -0.014359945        NA        NA
## 2007-01-08        NA         NA         NA  0.003874768        NA        NA
## 2007-01-09        NA         NA         NA  0.002161603        NA        NA
## 2007-01-10        NA         NA         NA  0.001078401        NA        NA
##              ClCl.SOXXa
## 2007-01-03           NA
## 2007-01-04  0.019562682
## 2007-01-05 -0.019026121
## 2007-01-08  0.003944806
## 2007-01-09  0.003601784
## 2007-01-10  0.017128858
```


ClCl.AOKa
ClCl.JPSTa
ClCl.GOVTa
ClCl.VBKa
ClCl.SCHa
ClCl.DRNa
ClCl.SOXXa
−0.010
0.005
−0.10
0.05
−0.4
0.0
−0.04
−0.02
0.0
−0.15
−0.010
−0.10
−0.4
0.2
−0.04
0.00
−0.02
0.01
0.0
0.6
−0.15
0.00




```
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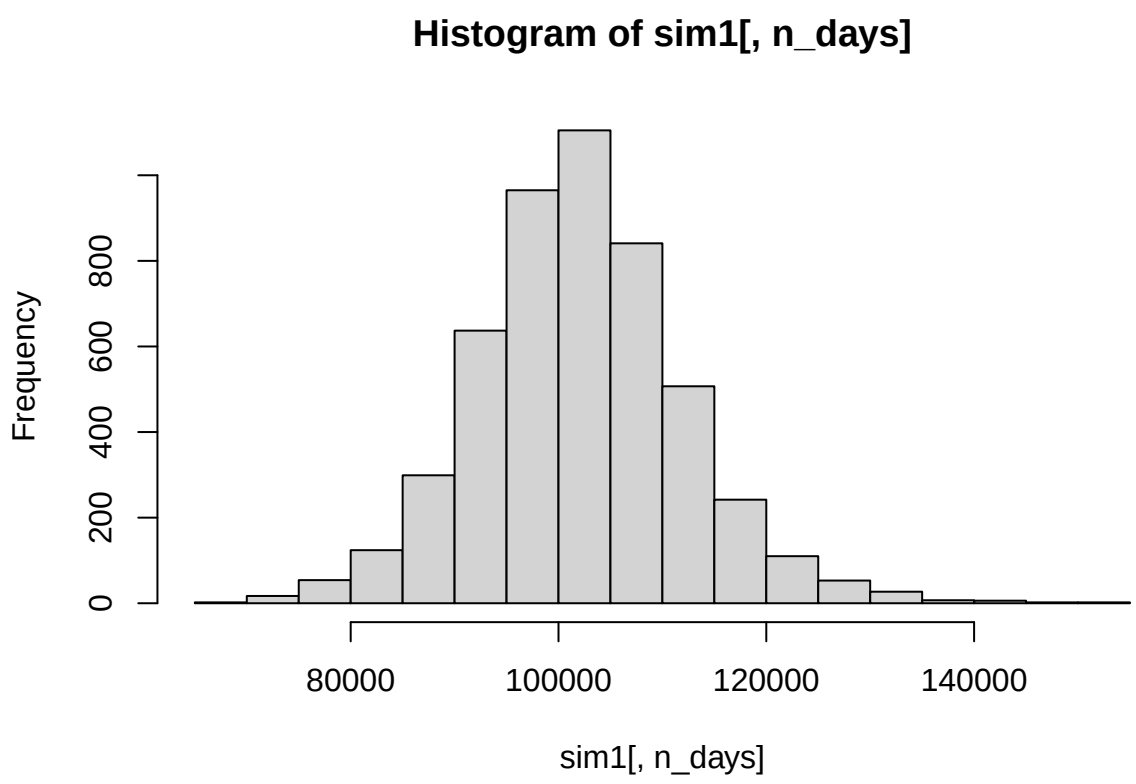
## period1=-2208988800&period2=1660521600&interval=1d&events=split'
```

```
##            VBK.Open VBK.High  VBK.Low VBK.Close VBK.Volume VBK.Adjusted
## 2017-06-01 139.1914 141.1713 139.1041  141.1713     124100     141.1713
## 2017-06-02 141.4139 142.3941 141.1713  142.0933     110900     142.0933
## 2017-06-05 142.0448 142.1127 141.2975  141.4333      94300     141.4333
## 2017-06-06 140.7637 141.8507 140.4531  141.2004     124000     141.2004
## 2017-06-07 141.3072 141.5692 140.6375  141.1810      69800     141.1810
## 2017-06-08 141.1034 142.2777 140.7249  142.0545     106000     142.0545
```

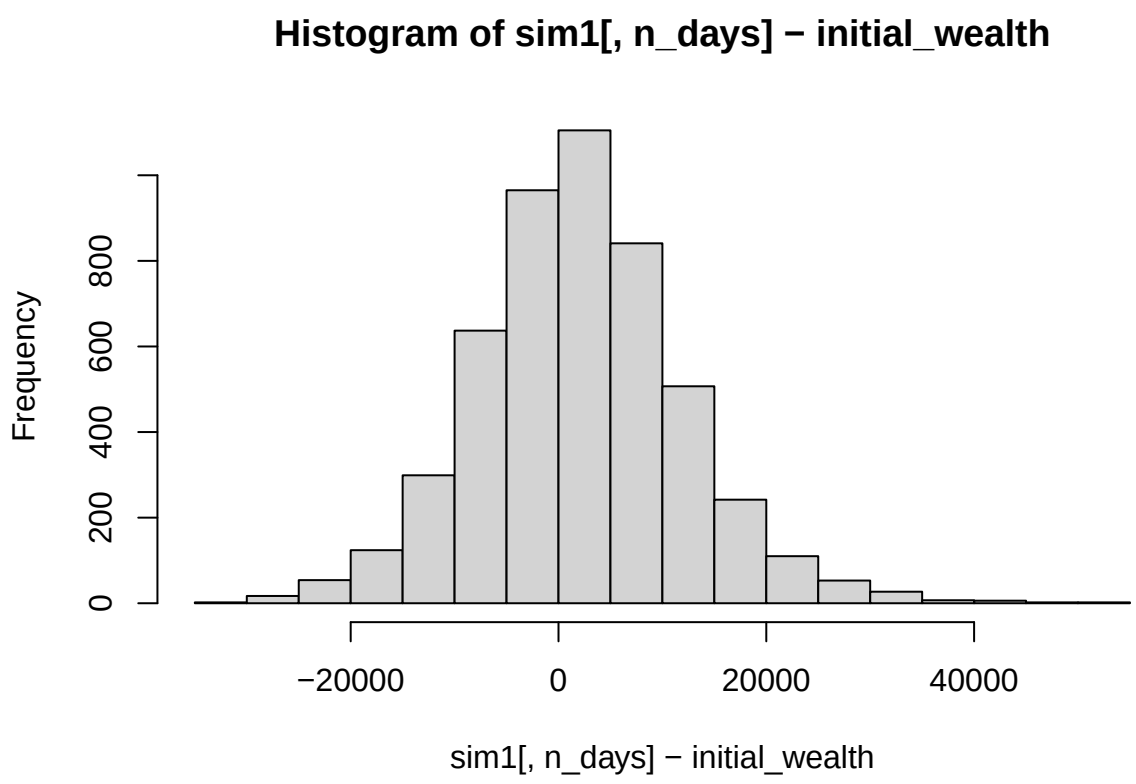
```
##            ClCl.VBKa     ClCl.SCHa ClCl.DRNa ClCl.SOXXa
## 2010-01-04        NA            NA        NA         NA
## 2010-01-05        NA  0.0026465028        NA         NA
## 2010-01-06        NA -0.0007541478        NA         NA
## 2010-01-07        NA  0.0030188679        NA         NA
## 2010-01-08        NA  0.0063957863        NA         NA
## 2010-01-11        NA  0.0003738318        NA         NA
```

```
##               [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## result.1 103244.20 102368.39 102308.45 103646.14 103853.15 104544.11 104439.18
## result.2  98777.64  98213.40  98898.86  98229.52  95572.32  94863.70  93798.23
## result.3 101175.20 103017.23 105599.52 105661.87 104301.12 106093.14 107355.81
## result.4  97997.16  97311.48  96152.78  98817.77  98901.70 101571.58 101137.90
## result.5  97621.09  97573.91  96227.95  95369.91  95598.60  94636.07  94547.38
## result.6 101235.62 103203.89 103453.24 103247.90 103021.87 104804.21 104009.95
##               [,8]      [,9]     [,10]     [,11]     [,12]     [,13]     [,14]
## result.1 104296.11 104215.99 103558.09 102941.63 104410.72 106806.45 104772.44
## result.2  96177.75  94017.11  92740.61  93185.11  92658.23  94110.88  94309.93
## result.3 108135.92 107797.63 107254.13 113747.99 112036.31 114506.84 114579.72
## result.4  98754.66  98357.54  98311.86  97436.35  98806.57  98687.24 101946.77
## result.5  95292.20  93238.84  93595.03  93306.52  92279.04  92873.53  95579.89
## result.6 103916.49 103558.11 104932.33 102645.15 100616.23 101336.61 100414.57
##              [,15]     [,16]     [,17]     [,18]     [,19]     [,20]
## result.1 105320.85 104929.82  95308.53  96441.61  95359.27  94977.15
## result.2  94270.33  94579.92  92048.57  90800.20  91410.18  91076.19
## result.3 113984.60 113033.76 113344.51 111670.04 110309.85 109574.53
## result.4 102576.90 103561.30 103148.85 103692.72 106955.95 107975.29
## result.5  96726.56  96034.01  94905.35  93371.31  93125.98  92978.61
## result.6 100845.21 102167.07 111351.87 110779.88 111421.18 111011.22
```




```
## [1] 102040.9
```

```
## [1] 2040.861
```




```
##        5%
## -13728.41
```

```
## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
## on 'https://query2.finance.yahoo.com/v7/finance/download/AOK?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'
```

```
## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
## on 'https://query1.finance.yahoo.com/v7/finance/download/AOK?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'
```

```
## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
## on 'https://query2.finance.yahoo.com/v7/finance/download/JPST?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'
```

```
## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
## on 'https://query2.finance.yahoo.com/v7/finance/download/JPST?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'
```

```
## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
```

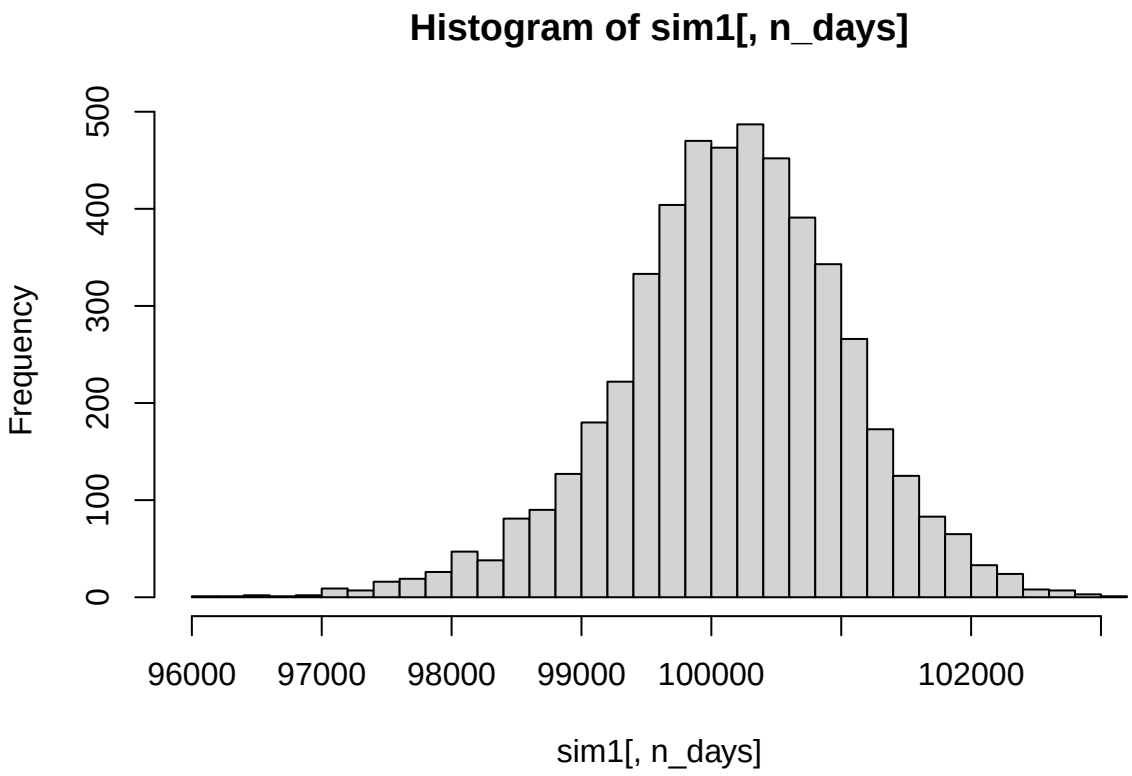
```
## on 'https://query2.finance.yahoo.com/v7/finance/download/GOVT?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'

## Warning in read.table(file = file, header = header, sep = sep,
## quote = quote, : incomplete final line found by readTableHeader
## on 'https://query1.finance.yahoo.com/v7/finance/download/GOVT?
## period1=-2208988800&period2=1660521600&interval=1d&events=split'

##            GOVT.Open GOVT.High GOVT.Low GOVT.Close GOVT.Volume GOVT.Adjusted
## 2017-06-01  23.13438  23.15270 23.10692   23.15270      677900      23.15270
## 2017-06-02  23.19847  23.23509 23.19847   23.21678      697500      23.21678
## 2017-06-05  23.18931  23.19847 23.18016   23.18931      672900      23.18931
## 2017-06-06  23.24424  23.24424 23.20762   23.24424      432000      23.24424
## 2017-06-07  23.21678  23.22593 23.18016   23.18931      393400      23.18931
## 2017-06-08  23.18931  23.18931 23.14354   23.18016      742600      23.18015

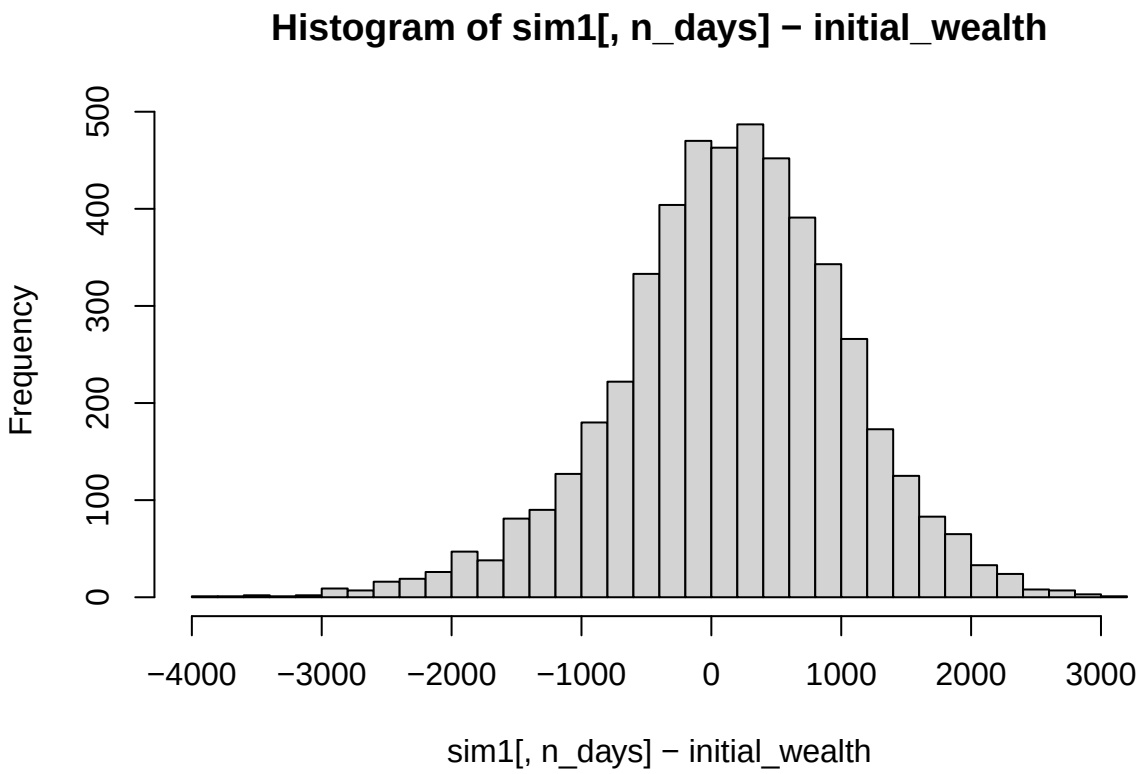
##                ClCl.AOKa   ClCl.JPSTa    ClCl.GOVTa
## 2017-06-02  0.0036464743 9.984019e-05  0.0027678923
## 2017-06-05 -0.0014649575 0.000000e+00 -0.0011830047
## 2017-06-06  0.0008802523 2.003396e-05  0.0023686932
## 2017-06-07 -0.0002932571 0.000000e+00 -0.0023630958
## 2017-06-08 -0.0011729326 2.796309e-04 -0.0003947888
## 2017-06-09 -0.0005871990 0.000000e+00 -0.0007899289

##               [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## result.1  99210.85  99119.24  98938.03  99125.27  99116.98  99063.15  98986.33
## result.2  99942.53 100098.71 100089.73 100255.40 100213.04 100287.16 100100.01
## result.3 100053.14 100646.46 100582.70 100469.29  99943.14  99882.73  99823.45
## result.4 100139.17 100129.42  99987.07  99815.04  99846.62 100056.36 100058.97
## result.5 100047.48 100275.25 100357.12 100367.95 100530.34 100572.12 100770.35
## result.6  99980.41  99990.88  99809.20  99479.89  99609.37  99596.77  99768.66
##               [,8]      [,9]     [,10]     [,11]     [,12]     [,13]     [,14]
## result.1  99157.48  99318.46  98948.29  99102.76  99090.58  99044.07  98984.39
## result.2 100030.52  99946.39  99968.57 100074.41 100042.70 100143.99 100125.87
## result.3  99588.63  99659.62  99708.91  99461.40  97525.87  97568.36  97953.33
## result.4 100031.18  99867.56 100037.62 100159.30 100157.95 100356.71 100254.44
## result.5 100759.39 100910.01 101101.80 101118.77 101214.08 101107.07 101101.96
## result.6  99677.30  99893.42  99555.21  99597.87  99657.19  99640.03  99353.69
##              [,15]     [,16]     [,17]     [,18]     [,19]     [,20]
## result.1  99139.01  99049.46  99078.33  98521.71  98405.08  98532.80
## result.2 100159.13 100131.41 100008.35 100042.02  99649.63  99675.03
## result.3  97930.00  98025.54  98125.44  97933.93  98160.47  98238.82
## result.4 100411.90 100535.09 100506.72 100681.52 100723.26 100649.21
## result.5 100895.66 100773.87 100722.51 100899.67 100652.03 100754.60
## result.6  99460.95  99580.49  98992.32  98977.26  99075.39  99140.92
```




```
## [1] 100150.6
```

```
## [1] 150.6183
```




```
##        5%
## -1399.222
```

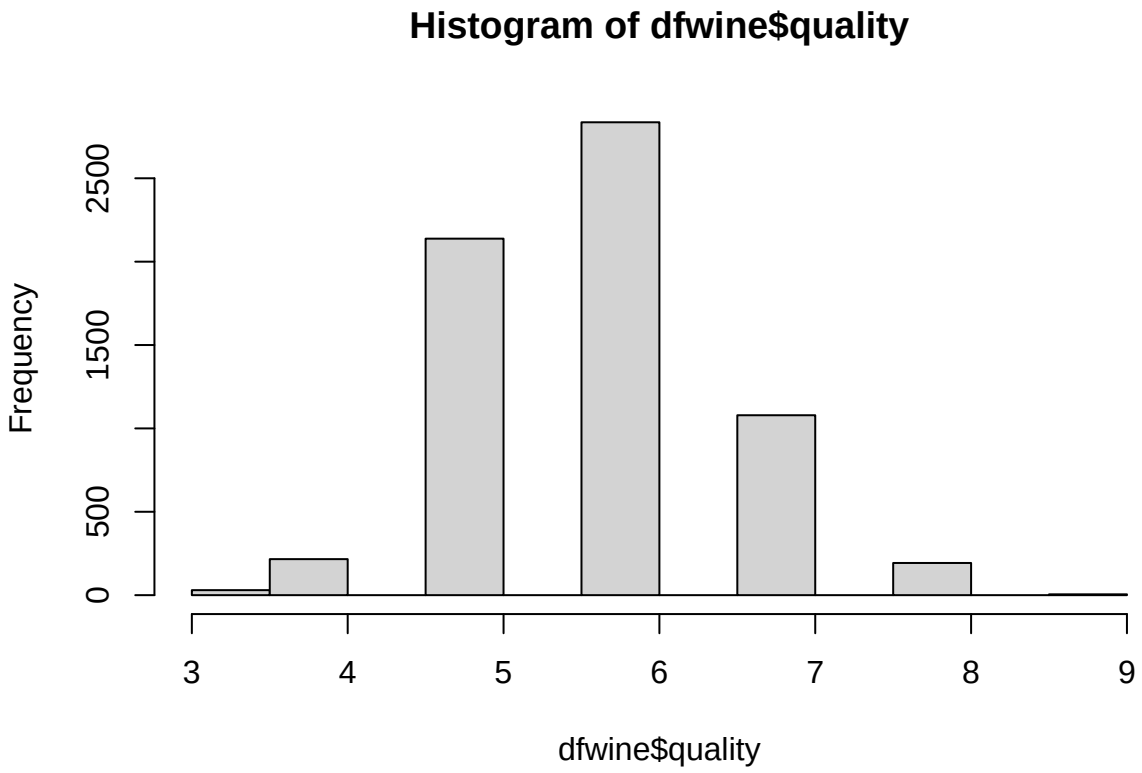
Comments: We chose to have two separate portfolios based off of aggressiveness vs. non-aggressiveness. The aggressive portfolio comprised of: VBK, SCHG, DRN, and SOXX. The safe portfolio comprised of: AOK, JPST, and GOVT.

The aggressive portfolio had a calculated mean profit of $102,109.40 over the year, with an expectation to gain around 2,109 dollars per day. Using a 5% value at risk means that out of our simulations performed, 95% of them will perform better than a loss of 13,078.49 dollars over a 4-week period.

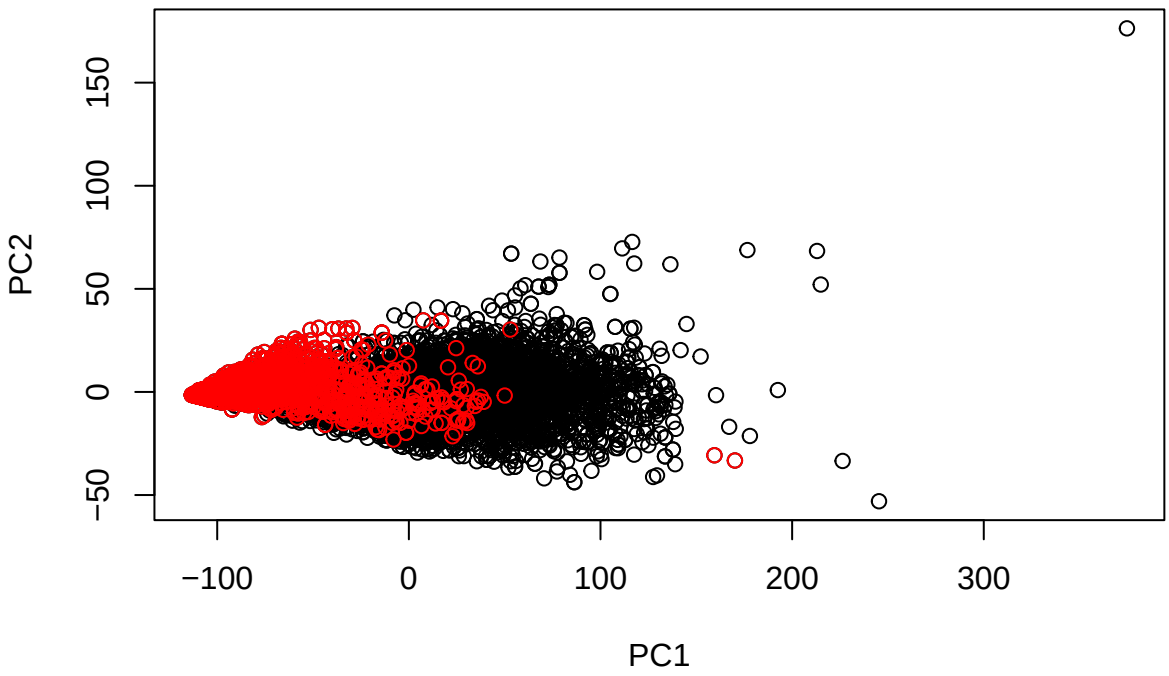
The safe portfolio had a calculated mean profit of $100,161.60 over the year, with an expectation to gain around 162 dollars per day. Using a 5% value at risk means that out of our simulations, 95% of them will perform better than a loss of 1,351.52 dollars over a 4-week period.

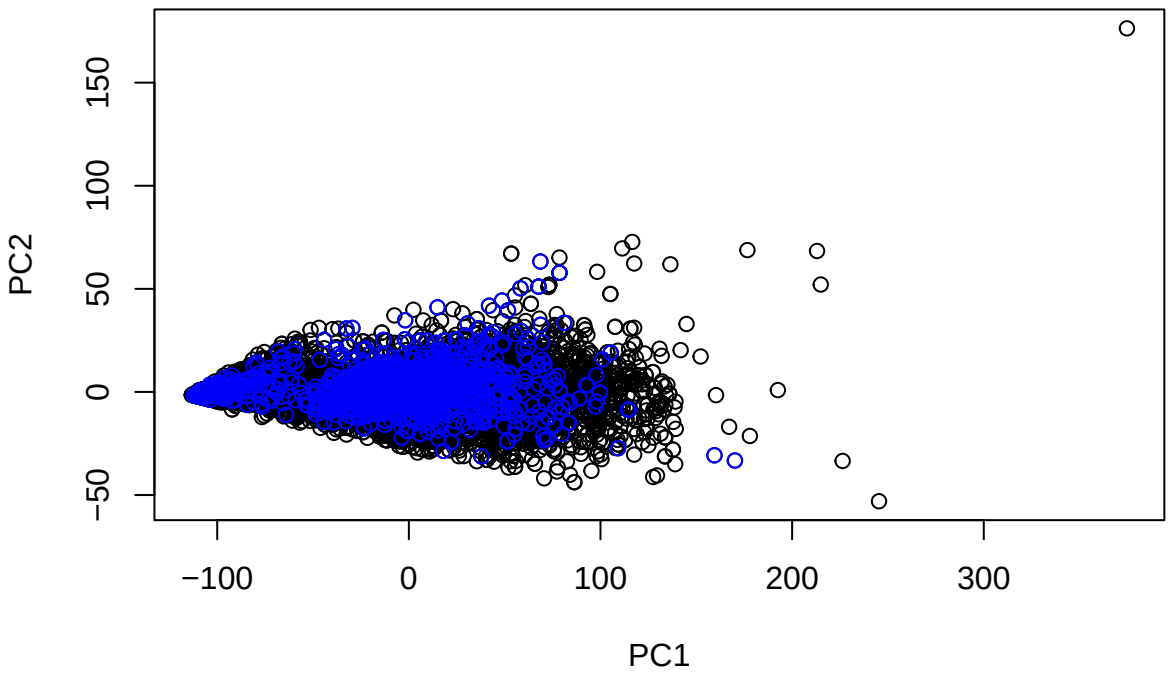
Out of our two portfolios, the aggressive portfolio returned a slightly higher mean profit over the year, although the daily amount gained per day vastly out-performed the safe portfolio (2,109 dollars vs. 162 dollars). Although the aggressive portfolio can incur better gains than the safe portfolio, the potential loss is also much greater than the safe portfolio (5% of simulations have a mean loss of 13,078.49 dollars vs. 1,351.52 dollars).

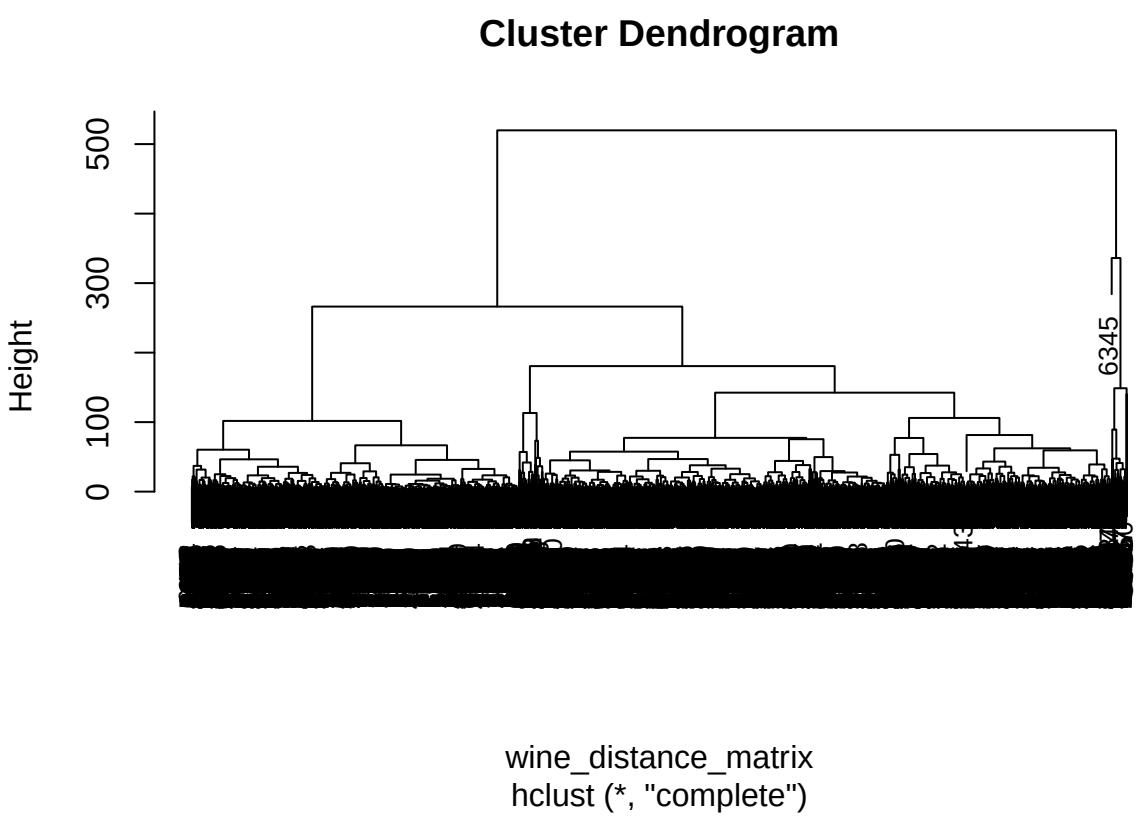
Clustering and PCA




```
##                              PC1           PC2           PC3
## fixed.acidity        -7.407964e-03 -5.365624e-03  0.0237980377
## volatile.acidity     -1.184329e-03 -7.844986e-04  0.0008841018
## citric.acid           4.868693e-04 -2.479470e-04  0.0019286942
## residual.sugar        4.101972e-02  1.863643e-02  0.9952741053
## chlorides            -1.681987e-04  6.726744e-05  0.0001730199
## free.sulfur.dioxide   2.304818e-01  9.726583e-01 -0.0272149098
## total.sulfur.dioxide  9.721668e-01 -2.314097e-01 -0.0358290013
## density               1.772339e-06  1.329966e-06  0.0004604088
## pH                   -6.555205e-04  6.479869e-04 -0.0069116181
## sulphates            -7.043386e-04  3.463575e-04 -0.0019352912
## alcohol              -5.451737e-03  2.850174e-03 -0.0823558184
```


PC2
150
100
50
0
−50
−100
0
100
200
300
PC1


PC2
150
100
50
0
−50
−100
0
100
200
300
PC1




```
##    1    2    3    4    5    6    7
## 2273 2385 1563  101  169    5    1
```

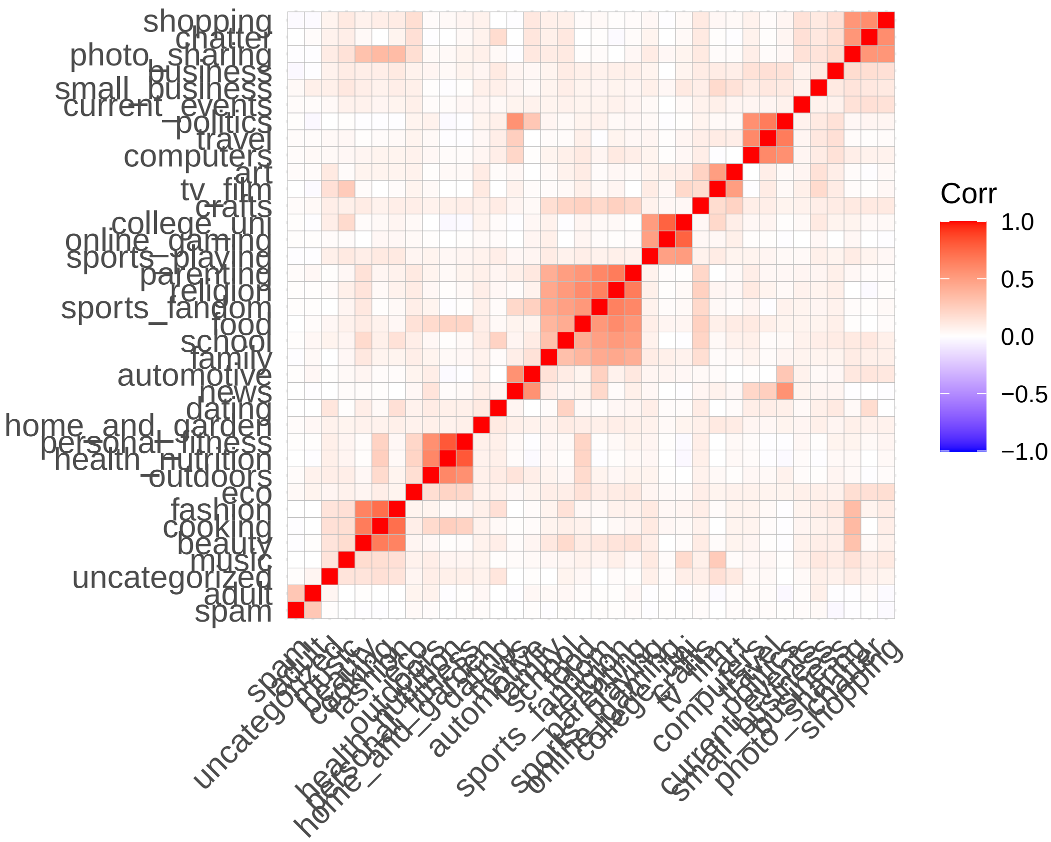
Comments: In our initial analysis, we plotted the histogram of quality values for the wines in our dataset to get an understanding of the distribution of the target variable. We then selected and scaled the 11 predictor variable values. Following that we defined the output variable values based on color (red) and quality (quality > 6 were chose as the high quality wines).

1] After the preliminary exploratory data analysis, we ran a PCA model with 2 principal components. Observations: 1. In regards to the wine color, the majority of red wines tend to have a PC1 value < 0 whereas most of the white wines had values > 0. This is a good indicator that positive values for PC1 indicate white as the wine color. 2. For the quality of the wine, the distinction was not that clear from the plot. However, we did find that almost all he higher quality wines had PC1 values < 100. 3. Overall, the PC1 proved to be quite significant in segregating wines based on their color and to some extent, the quality as well.

2] After implementing PCA, we tried heirarchical clustering on the dataset. Observations and Key Points: 1. We decided to proceed with 7 clusters with linkage factor as 'complete'. 2. The cluster dendogram was extremely convoluted with numerous splits suggesting that heirarchical clustering might not be the optimal choice in this test case. 3. The end results from clustering were very sensitive to outliers with only a few observations making up some of the clusters. There were no obvious actionable insights that were drawn from the results.

Market segmentation

```
##                          PC1           PC2
## chatter           8.377923e-02  6.174357e-01
## current_events    1.674083e-02  5.633466e-02
## travel            7.694647e-03  1.026362e-01
## photo_sharing     1.319231e-01  4.784651e-01
## uncategorized     2.524063e-02  2.637812e-02
## tv_film           5.842740e-03  3.273925e-02
## sports_fandom     2.149987e-02  5.981140e-02
## politics          7.858764e-03  1.707149e-01
## food              9.520239e-02  1.097888e-02
## family            1.999472e-02  4.337977e-02
## home_and_garden   1.529762e-02  1.890571e-02
## music             2.478241e-02  4.490862e-02
## news              1.821436e-02  6.362012e-02
## online_gaming     1.581928e-02  1.210238e-01
## shopping          5.245830e-02  2.497367e-01
## health_nutrition  8.084217e-01 -2.731887e-01
## college_uni       5.810219e-03  1.672739e-01
## sports_playing    1.942244e-02  4.783238e-02
## cooking           3.404963e-01  2.701636e-01
## eco               3.918988e-02  2.448001e-02
## computers         1.599136e-02  6.154333e-02
## business          1.321910e-02  3.705721e-02
## outdoors          1.446150e-01 -3.628227e-02
## crafts            2.138903e-02  2.954968e-02
## automotive        6.331646e-03  7.134999e-02
## art               1.932288e-02  2.483807e-02
## religion          2.785915e-02  3.742165e-02
## beauty            6.000130e-02  1.107477e-01
## parenting         2.929342e-02  4.023737e-02
## dating            3.977599e-02  6.351116e-02
## school            2.176039e-02  5.556398e-02
## personal_fitness  3.873704e-01 -1.057094e-01
## fashion           9.682483e-02  1.739817e-01
## small_business    5.570533e-03  2.839783e-02
## spam              4.113457e-05  1.035245e-05
## adult            -4.331520e-04  2.488791e-03
```




```
##    1    2    3    4    5    6    7
##  397 3686  607  557  493  933 1209

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

## Warning in mean.default(x, ..., na.rm = na.rm): argument is not numeric or
## logical: returning NA

##   Clustering..K.Means.     Max1..K.Means.     Max2..K.Means.   Max3..K.Means.
```

```
## 1                    1          chatter_1    photo_sharing_1         travel_1
## 2                    2          cooking_1    photo_sharing_1        fashion_1
## 3                    3 health_nutrition_1 personal_fitness_1        cooking_1
## 4                    4      college_uni_1    online_gaming_1  photo_sharing_1
## 5                    5          chatter_1    photo_sharing_1 current_events_1
## 6                    6         politics_1           travel_1           news_1
## 7                    7    sports_fandom_1         religion_1           food_1
##   Original.Groups..Correaltion.Plot.Analysis.
## 1                                    Group 7
## 2                                    Group 2
## 3                                    Group 3
## 4                                    Group 5
## 5                                    Group 7
## 6                                    Group 6
## 7                                    Group 4
```

Correlation Plot: We began by looking at a simple correlation plot, to see if we could identify any interesting relationships between the different areas of interest. Based on our intuition and understanding of the correlation plot, we concluded there were 7 groups of correlation features that we listed below.

- Group 1 - Bots: adult and spam highly correlated
- Group 2 - fashion, cooking, and beauty
- Group 3 - personal fitness, health nutrition, outdoors
- Group 4 - Parenting, religion, sports_fandom, food, school, family
- Group 5 - college_uni, online_gaming, sports_playing
- Group 6 - politics, travel, computers
- Group 7 - shopping, chatter, photo_sharing

K-Means: Once we established these groups we ran a k-means model to see if we would get clusters that had the same, or similar features to the ones in our initial groups. We average the different amount of tweets for each area of interest in each cluster. We then selected the 3 highest feature averages from each group. We used these three features in each to determine if the clusters determined by kmeans were similarly defined to the groups we had identified using the correlation plot.

Result: As seen in our last data frame (comparison), 6 out of the 7 clusters seemed to have a match with our original groups.The only original group we could not find a match for was Group 1. However, the other 6 clusters/groups are incredibly valuable because they can serve a guides for different market segments that the company can cater to. For example, Group 3 is all about being active and healthy, so that group can now be target marketed to in a way that serves those interests.

The Reuters corpus

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

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

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

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

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

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

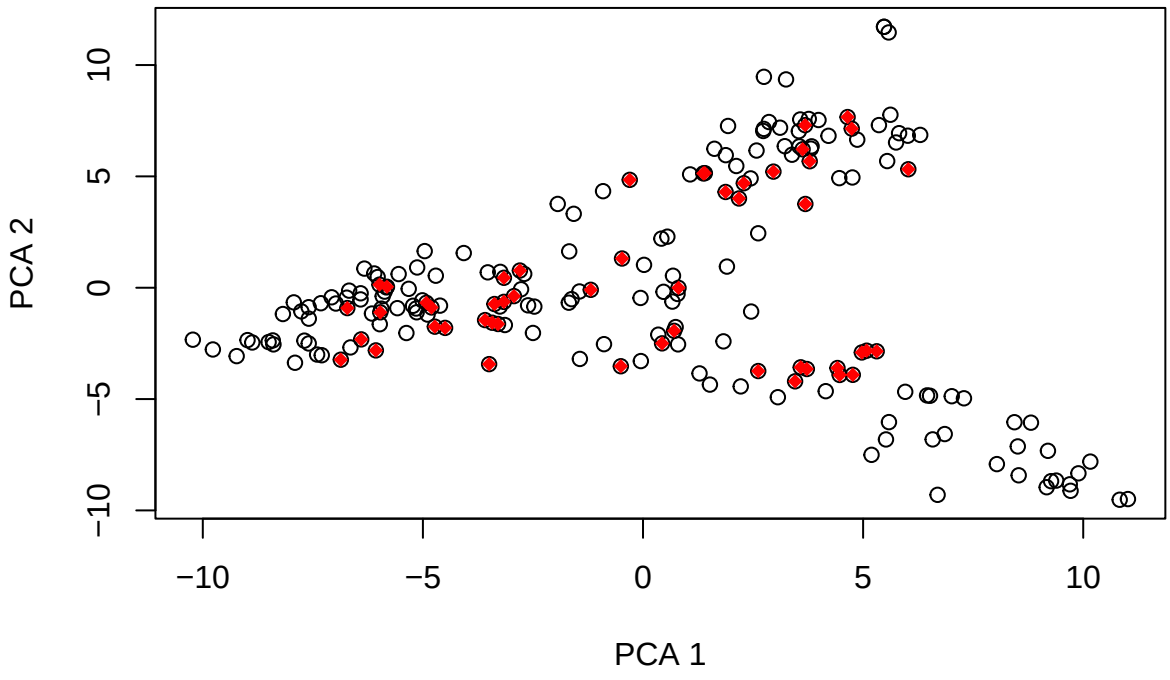
## Warning in tm_map.SimpleCorpus(my_documents,
## content_transformer(removeNumbers)): transformation drops documents

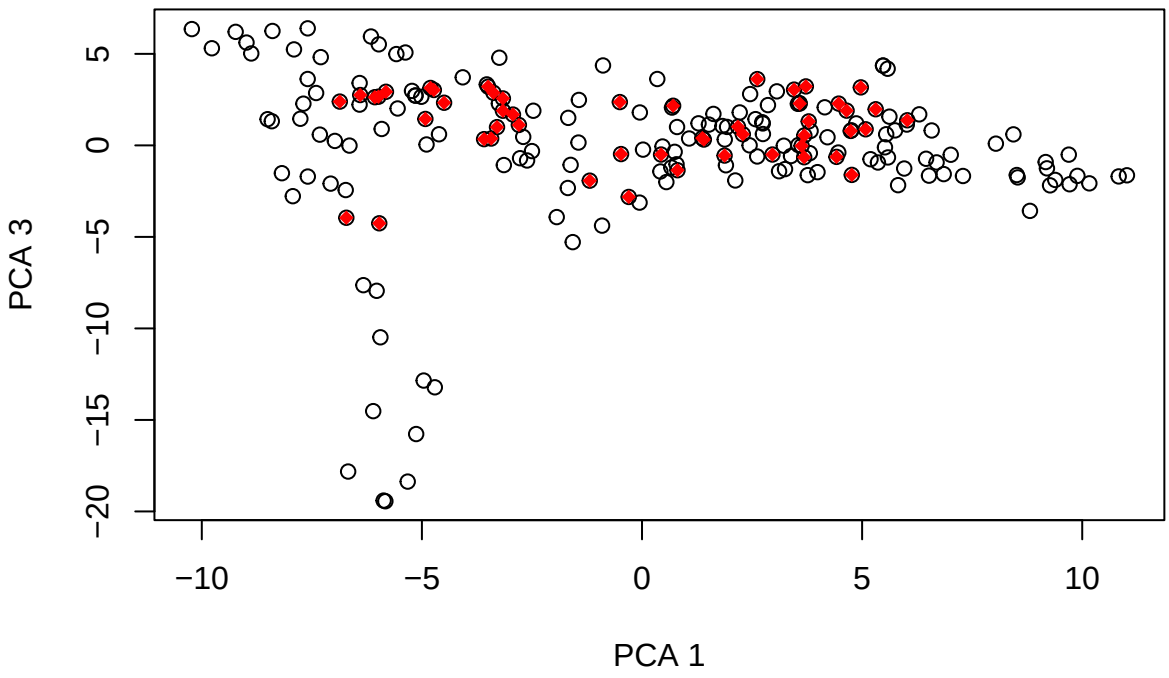
## Warning in tm_map.SimpleCorpus(my_documents,
## content_transformer(removePunctuation)): transformation drops documents

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

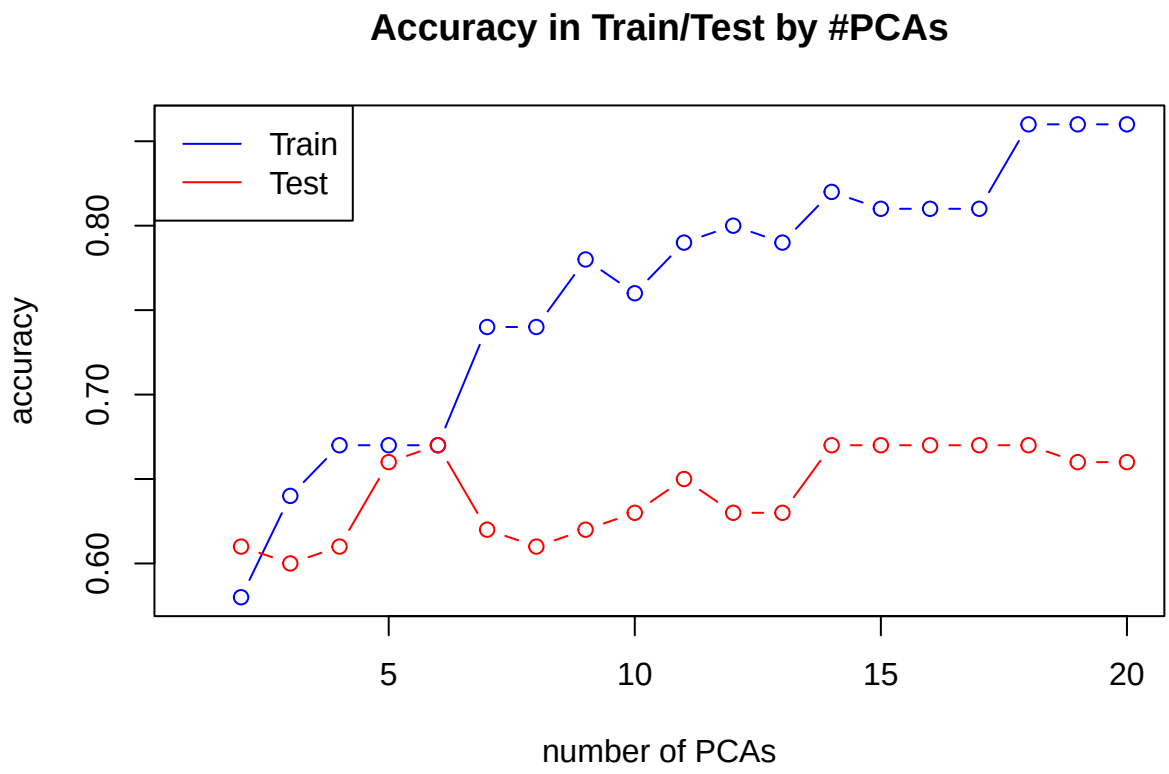
## Warning in tm_map.SimpleCorpus(my_documents, content_transformer(removeWords), :
## transformation drops documents

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.3186  0.4307  0.4983  0.6097  3.1179
```






```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.3018  0.4107  0.4836  0.5701  2.7663
```



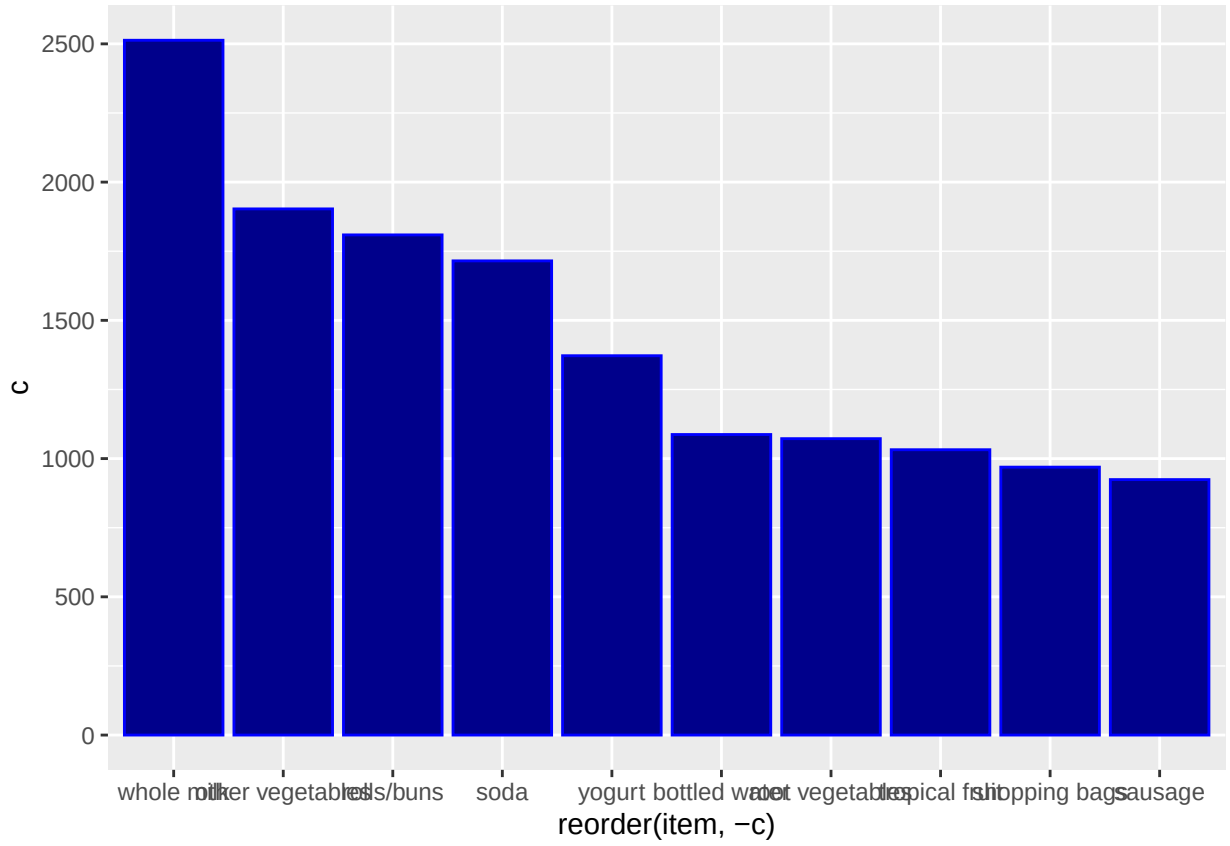
Comments:
Comments: Question: Are we able to distinguish who wrote a document based on the content and words of that document itself?

Approach: For this problem, we selected documents of four authors: Simon Cowell, Aaron Pressman, Joe Ortiz, and William Kazer, in Train and Test. So, using analytical tools, can we recognize which documents were written by Simon Cowell and which were not? First of all, we began our approach with a Text Analysis. As we learn in class, the first step is converting the unstructured data into a structured one. So, to begin we tokenized the strings and symbols, then we removed stop words and useless characters, and finally we have got DTM matrix and TFIDF weights. Now, we get our data structured.

Results: Second, to address the question above, we ran a PCA. When we plotted the first and second principal components, we observed that there is no clear pattern to distinguish which documents were written by Simon Cowell, and on the first versus third principal components plot we can't distinguish a clear pattern either. Finally, we ran Logistic regression models using the first principal components as predictors (iterating from 2 to 20 PC). We can observe that as we increase the number of principal components as predictors, the accuracy increases in Train to distinguish written documents by Simon Cowell. However, in the Test set the accuracy become flat after the 6 number of principal components, reaching 64% accuracy on average, which is quite low.

Conclusion: To conclude, after using different analytical tools to distinguish written documents, we can say that it is difficult that task to make document discrimination. However, we can highlight that although the results were not top notch, it is probable that if we extend the analysis more in deep and trying different other predictive methods and different authors, we might get better outcomes.

Association rule mining




```
## transactions as itemMatrix in sparse format with
##  15296 rows (elements/itemsets/transactions) and
##  169 columns (items) and a density of 0.01677625
##
## most frequent items:
##       whole milk other vegetables       rolls/buns             soda
##             2513             1903             1809             1715
##           yogurt          (Other)
##             1372            34055
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4
## 3485 2630 2102 7079
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   2.835   4.000   4.000
##
## includes extended item information - examples:
##             labels
## 1 abrasive cleaner
## 2 artif. sweetener
## 3   baby cosmetics
```

```
##
## includes extended transaction information - examples:
##   transactionID
## 1             1
## 2             2
## 3             3

## 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
## [1]   {}                              => {soda}               0.112120816
## [2]   {}                              => {rolls/buns}         0.118266213
## [3]   {}                              => {other vegetables}   0.124411611
## [4]   {}                              => {whole milk}         0.164291318
## [5]   {butter milk}                   => {whole milk}         0.005033996
## [6]   {onions}                        => {root vegetables}    0.005295502
## [7]   {onions}                        => {other vegetables}   0.007452929
## [8]   {onions}                        => {whole milk}         0.005360879
## [9]   {berries}                       => {other vegetables}   0.005164749
## [10]  {berries}                       => {whole milk}         0.005230126
## [11]  {hamburger meat}                => {other vegetables}   0.006210774
## [12]  {hamburger meat}                => {whole milk}         0.005818515
## [13]  {dessert}                       => {whole milk}         0.006603033
## [14]  {cream cheese }                 => {yogurt}             0.005033996
## [15]  {chocolate}                     => {soda}               0.005360879
## [16]  {chicken}                       => {other vegetables}   0.007975941
## [17]  {chicken}                       => {whole milk}         0.006341527
## [18]  {frozen vegetables}             => {whole milk}         0.005687762
## [19]  {canned beer}                   => {soda}               0.006537657
## [20]  {beef}                          => {citrus fruit}       0.005099372
## [21]  {beef}                          => {root vegetables}    0.008695084
## [22]  {root vegetables}               => {beef}               0.008695084
## [23]  {beef}                          => {other vegetables}   0.008302824
## [24]  {beef}                          => {whole milk}         0.008172071
```

```
## [25]  {curd}                          => {yogurt}             0.007649059
## [26]  {curd}                          => {other vegetables}   0.007060669
## [27]  {curd}                          => {whole milk}         0.012617678
## [28]  {margarine}                     => {rolls/buns}         0.005491632
## [29]  {butter}                        => {yogurt}             0.006210774
## [30]  {butter}                        => {other vegetables}   0.008237448
## [31]  {butter}                        => {whole milk}         0.014382845
## [32]  {pork}                          => {root vegetables}    0.006733787
## [33]  {pork}                          => {other vegetables}   0.009283473
## [34]  {pork}                          => {whole milk}         0.008695084
## [35]  {frankfurter}                   => {sausage}            0.006472280
## [36]  {sausage}                       => {frankfurter}        0.006472280
## [37]  {frankfurter}                   => {tropical fruit}     0.005557008
## [38]  {frankfurter}                   => {rolls/buns}         0.006210774
## [39]  {frankfurter}                   => {other vegetables}   0.007060669
## [40]  {frankfurter}                   => {whole milk}         0.008237448
## [41]  {bottled beer}                  => {bottled water}      0.006929916
## [42]  {bottled beer}                  => {soda}               0.008302824
## [43]  {brown bread}                   => {pastry}             0.005033996
## [44]  {brown bread}                   => {rolls/buns}         0.006276151
## [45]  {brown bread}                   => {whole milk}         0.006733787
## [46]  {domestic eggs}                 => {rolls/buns}         0.008172071
## [47]  {domestic eggs}                 => {whole milk}         0.008172071
## [48]  {fruit/vegetable juice}         => {bottled water}      0.005753138
## [49]  {fruit/vegetable juice}         => {soda}               0.009348849
## [50]  {shopping bags}                 => {soda}               0.006406904
## [51]  {whipped/sour cream}            => {yogurt}             0.009741109
## [52]  {yogurt}                        => {whipped/sour cream} 0.009741109
## [53]  {whipped/sour cream}            => {rolls/buns}         0.005360879
## [54]  {whipped/sour cream}            => {other vegetables}   0.008302824
## [55]  {whipped/sour cream}            => {whole milk}         0.011440900
## [56]  {pip fruit}                     => {citrus fruit}       0.008172071
## [57]  {citrus fruit}                  => {pip fruit}          0.008172071
## [58]  {pip fruit}                     => {sausage}            0.006210774
## [59]  {sausage}                       => {pip fruit}          0.006210774
## [60]  {pip fruit}                     => {tropical fruit}     0.012683054
## [61]  {tropical fruit}                => {pip fruit}          0.012683054
## [62]  {pip fruit}                     => {root vegetables}    0.008106695
## [63]  {root vegetables}               => {pip fruit}          0.008106695
## [64]  {pip fruit}                     => {other vegetables}   0.010917887
## [65]  {pip fruit}                     => {whole milk}         0.012552301
## [66]  {pastry}                        => {soda}               0.007256799
## [67]  {pastry}                        => {rolls/buns}         0.010198745
## [68]  {pastry}                        => {whole milk}         0.009414226
## [69]  {citrus fruit}                  => {sausage}            0.006929916
## [70]  {sausage}                       => {citrus fruit}       0.006929916
## [71]  {citrus fruit}                  => {tropical fruit}     0.012486925
## [72]  {tropical fruit}                => {citrus fruit}       0.012486925
## [73]  {citrus fruit}                  => {root vegetables}    0.008695084
## [74]  {root vegetables}               => {citrus fruit}       0.008695084
## [75]  {citrus fruit}                  => {yogurt}             0.006733787
## [76]  {citrus fruit}                  => {other vegetables}   0.012813808
## [77]  {other vegetables}              => {citrus fruit}       0.012813808
## [78]  {citrus fruit}                  => {whole milk}         0.012813808
```

```
## [79]  {sausage}                                => {tropical fruit}     0.008172071
## [80]  {tropical fruit}                         => {sausage}            0.008172071
## [81]  {sausage}                                => {root vegetables}    0.007322176
## [82]  {root vegetables}                        => {sausage}            0.007322176
## [83]  {sausage}                                => {rolls/buns}         0.010787134
## [84]  {sausage}                                => {other vegetables}   0.012617678
## [85]  {other vegetables}                       => {sausage}            0.012617678
## [86]  {sausage}                                => {whole milk}         0.012552301
## [87]  {bottled water}                          => {soda}               0.014644351
## [88]  {soda}                                   => {bottled water}      0.014644351
## [89]  {bottled water}                          => {rolls/buns}         0.008564331
## [90]  {tropical fruit}                         => {root vegetables}    0.010983264
## [91]  {root vegetables}                        => {tropical fruit}     0.010983264
## [92]  {tropical fruit}                         => {yogurt}             0.008172071
## [93]  {tropical fruit}                         => {other vegetables}   0.015494247
## [94]  {other vegetables}                       => {tropical fruit}     0.015494247
## [95]  {tropical fruit}                         => {whole milk}         0.018305439
## [96]  {whole milk}                             => {tropical fruit}     0.018305439
## [97]  {root vegetables}                        => {other vegetables}   0.025366109
## [98]  {other vegetables}                       => {root vegetables}    0.025366109
## [99]  {root vegetables}                        => {whole milk}         0.022620293
## [100] {whole milk}                             => {root vegetables}    0.022620293
## [101] {yogurt}                                 => {rolls/buns}         0.011898536
## [102] {rolls/buns}                             => {yogurt}             0.011898536
## [103] {yogurt}                                 => {other vegetables}   0.015886506
## [104] {other vegetables}                       => {yogurt}             0.015886506
## [105] {yogurt}                                 => {whole milk}         0.024254707
## [106] {whole milk}                             => {yogurt}             0.024254707
## [107] {soda}                                   => {rolls/buns}         0.014252092
## [108] {rolls/buns}                             => {soda}               0.014252092
## [109] {rolls/buns}                             => {whole milk}         0.018305439
## [110] {whole milk}                             => {rolls/buns}         0.018305439
## [111] {other vegetables}                       => {whole milk}         0.040860356
## [112] {whole milk}                             => {other vegetables}   0.040860356
## [113] {other vegetables, root vegetables}      => {whole milk}         0.008172071
## [114] {root vegetables, whole milk}            => {other vegetables}   0.008172071
## [115] {other vegetables, whole milk}           => {root vegetables}    0.008172071
## [116] {other vegetables, yogurt}               => {whole milk}         0.006341527
## [117] {whole milk, yogurt}                     => {other vegetables}   0.006341527
## [118] {other vegetables, whole milk}           => {yogurt}             0.006341527
##       confidence coverage   lift      count
## [1]   0.1121208  1.00000000 1.0000000 1715
## [2]   0.1182662  1.00000000 1.0000000 1809
## [3]   0.1244116  1.00000000 1.0000000 1903
## [4]   0.1642913  1.00000000 1.0000000 2513
## [5]   0.2800000  0.01797856 1.7042897   77
## [6]   0.2655738  0.01993985 3.7893810   81
## [7]   0.3737705  0.01993985 3.0043055  114
## [8]   0.2688525  0.01993985 1.6364374   82
## [9]   0.2415902  0.02137814 1.9418623   79
## [10]  0.2446483  0.02137814 1.4891129   80
## [11]  0.2905199  0.02137814 2.3351508   95
## [12]  0.2721713  0.02137814 1.6566381   89
## [13]  0.2767123  0.02386245 1.6842785  101
```

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## [14]  0.1974359  0.02549686 2.2011512   77
## [15]  0.1680328  0.03190377 1.4986761   82
## [16]  0.2890995  0.02758891 2.3237343  122
## [17]  0.2298578  0.02758891 1.3990868   97
## [18]  0.1839323  0.03092312 1.1195500   87
## [19]  0.1308901  0.04994770 1.1674019  100
## [20]  0.1511628  0.03373431 2.8405234   78
## [21]  0.2577519  0.03373431 3.6777739  133
## [22]  0.1240672  0.07008368 3.6777739  133
## [23]  0.2461240  0.03373431 1.9783044  127
## [24]  0.2422481  0.03373431 1.4745031  125
## [25]  0.2232824  0.03425732 2.4893063  117
## [26]  0.2061069  0.03425732 1.6566530  108
## [27]  0.3683206  0.03425732 2.2418751  193
## [28]  0.1458333  0.03765690 1.2330938   84
## [29]  0.1743119  0.03563023 1.9433493   95
## [30]  0.2311927  0.03563023 1.8582885  126
## [31]  0.4036697  0.03563023 2.4570363  220
## [32]  0.1816578  0.03706851 2.5920135  103
## [33]  0.2504409  0.03706851 2.0130028  142
## [34]  0.2345679  0.03706851 1.4277559  133
## [35]  0.1706897  0.03791841 2.8256158   99
## [36]  0.1071429  0.06040795 2.8256158   99
## [37]  0.1465517  0.03791841 2.1721465   85
## [38]  0.1637931  0.03791841 1.3849526   95
## [39]  0.1862069  0.03791841 1.4967003  108
## [40]  0.2172414  0.03791841 1.3222937  126
## [41]  0.1338384  0.05177824 1.8833412  106
## [42]  0.1603535  0.05177824 1.4301852  127
## [43]  0.1206897  0.04171025 2.1097931   77
## [44]  0.1504702  0.04171025 1.2723010   96
## [45]  0.1614420  0.04171025 0.9826570  103
## [46]  0.2003205  0.04079498 1.6938102  125
## [47]  0.2003205  0.04079498 1.2193007  125
## [48]  0.1237693  0.04648274 1.7416521   88
## [49]  0.2011252  0.04648274 1.7938255  143
## [50]  0.1011352  0.06334990 0.9020198   98
## [51]  0.2113475  0.04609048 2.3562475  149
## [52]  0.1086006  0.08969665 2.3562475  149
## [53]  0.1163121  0.04609048 0.9834766   82
## [54]  0.1801418  0.04609048 1.4479504  127
## [55]  0.2482270  0.04609048 1.5108951  175
## [56]  0.1680108  0.04864017 3.1571161  125
## [57]  0.1535627  0.05321653 3.1571161  125
## [58]  0.1276882  0.04864017 2.1137644   95
## [59]  0.1028139  0.06040795 2.1137644   95
## [60]  0.2607527  0.04864017 3.8647995  194
## [61]  0.1879845  0.06746862 3.8647995  194
## [62]  0.1666667  0.04864017 2.3781095  124
## [63]  0.1156716  0.07008368 2.3781095  124
## [64]  0.2244624  0.04864017 1.8041915  167
## [65]  0.2580645  0.04864017 1.5707739  192
## [66]  0.1268571  0.05720450 1.1314326  111
## [67]  0.1782857  0.05720450 1.5074949  156
```

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## [68]  0.1645714  0.05720450 1.0017050  144
## [69]  0.1302211  0.05321653 2.1556952  106
## [70]  0.1147186  0.06040795 2.1556952  106
## [71]  0.2346437  0.05321653 3.4778203  191
## [72]  0.1850775  0.06746862 3.4778203  191
## [73]  0.1633907  0.05321653 2.3313653  133
## [74]  0.1240672  0.07008368 2.3313653  133
## [75]  0.1265356  0.05321653 1.4107062  103
## [76]  0.2407862  0.05321653 1.9354001  196
## [77]  0.1029953  0.12441161 1.9354001  196
## [78]  0.2407862  0.05321653 1.4656054  196
## [79]  0.1352814  0.06040795 2.0051008  125
## [80]  0.1211240  0.06746862 2.0051008  125
## [81]  0.1212121  0.06040795 1.7295341  112
## [82]  0.1044776  0.07008368 1.7295341  112
## [83]  0.1785714  0.06040795 1.5099108  165
## [84]  0.2088745  0.06040795 1.6788984  193
## [85]  0.1014188  0.12441161 1.6788984  193
## [86]  0.2077922  0.06040795 1.2647790  192
## [87]  0.2060718  0.07106433 1.8379438  224
## [88]  0.1306122  0.11212082 1.8379438  224
## [89]  0.1205152  0.07106433 1.0190161  131
## [90]  0.1627907  0.06746862 2.3228046  168
## [91]  0.1567164  0.07008368 2.3228046  168
## [92]  0.1211240  0.06746862 1.3503740  125
## [93]  0.2296512  0.06746862 1.8458982  237
## [94]  0.1245402  0.12441161 1.8458982  237
## [95]  0.2713178  0.06746862 1.6514435  280
## [96]  0.1114206  0.16429132 1.6514435  280
## [97]  0.3619403  0.07008368 2.9092164  388
## [98]  0.2038886  0.12441161 2.9092164  388
## [99]  0.3227612  0.07008368 1.9645663  346
## [100] 0.1376840  0.16429132 1.9645663  346
## [101] 0.1326531  0.08969665 1.1216480  182
## [102] 0.1006081  0.11826621 1.1216480  182
## [103] 0.1771137  0.08969665 1.4236107  243
## [104] 0.1276931  0.12441161 1.4236107  243
## [105] 0.2704082  0.08969665 1.6459066  371
## [106] 0.1476323  0.16429132 1.6459066  371
## [107] 0.1271137  0.11212082 1.0748099  218
## [108] 0.1205086  0.11826621 1.0748099  218
## [109] 0.1547816  0.11826621 0.9421170  280
## [110] 0.1114206  0.16429132 0.9421170  280
## [111] 0.3284288  0.12441161 1.9990636  625
## [112] 0.2487067  0.16429132 1.9990636  625
## [113] 0.3221649  0.02536611 1.9609371  125
## [114] 0.3612717  0.02262029 2.9038421  125
## [115] 0.2000000  0.04086036 2.8537313  125
## [116] 0.3991770  0.01588651 2.4296899   97
## [117] 0.2614555  0.02425471 2.1015364   97
## [118] 0.1552000  0.04086036 1.7302764   97
```

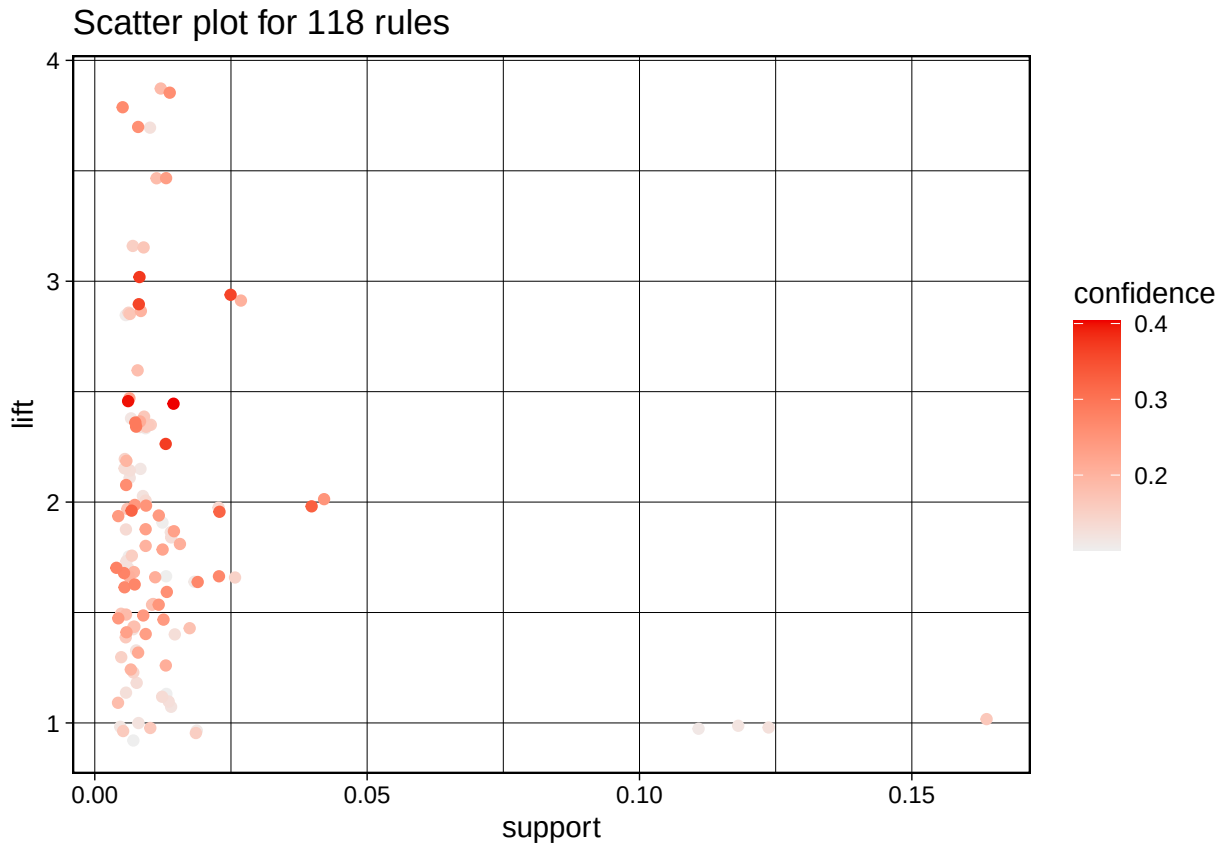
```
##      lhs                rhs                support     confidence coverage
## [1]  {onions}        => {root vegetables}  0.005295502 0.2655738  0.01993985
```

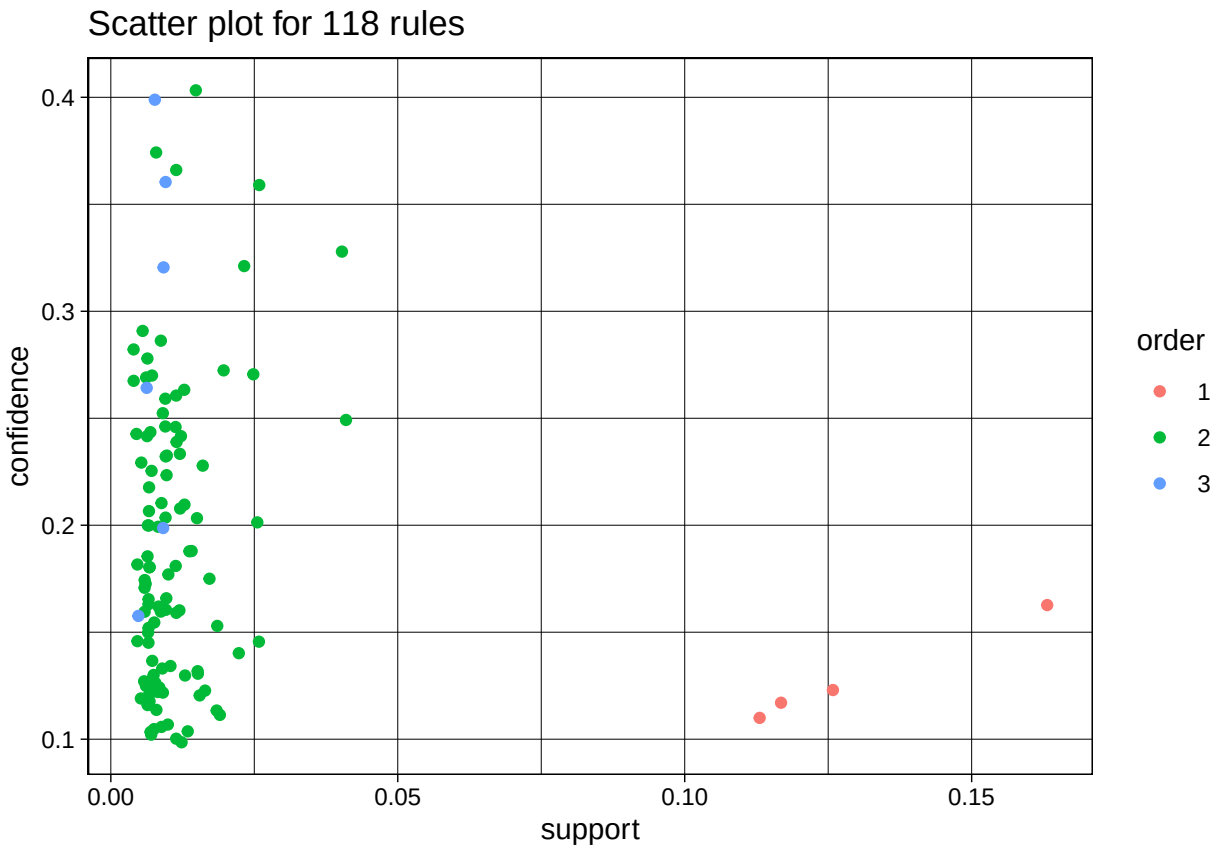
```
## [2]  {onions}          => {other vegetables} 0.007452929 0.3737705  0.01993985
## [3]  {beef}            => {root vegetables}  0.008695084 0.2577519  0.03373431
## [4]  {root vegetables} => {beef}             0.008695084 0.1240672  0.07008368
## [5]  {pip fruit}       => {citrus fruit}     0.008172071 0.1680108  0.04864017
## [6]  {citrus fruit}    => {pip fruit}        0.008172071 0.1535627  0.05321653
## [7]  {pip fruit}       => {tropical fruit}   0.012683054 0.2607527  0.04864017
## [8]  {tropical fruit}  => {pip fruit}        0.012683054 0.1879845  0.06746862
## [9]  {citrus fruit}    => {tropical fruit}   0.012486925 0.2346437  0.05321653
## [10] {tropical fruit}  => {citrus fruit}     0.012486925 0.1850775  0.06746862
##      lift     count
## [1]  3.789381  81
## [2]  3.004306 114
## [3]  3.677774 133
## [4]  3.677774 133
## [5]  3.157116 125
## [6]  3.157116 125
## [7]  3.864800 194
## [8]  3.864800 194
## [9]  3.477820 191
## [10] 3.477820 191
```

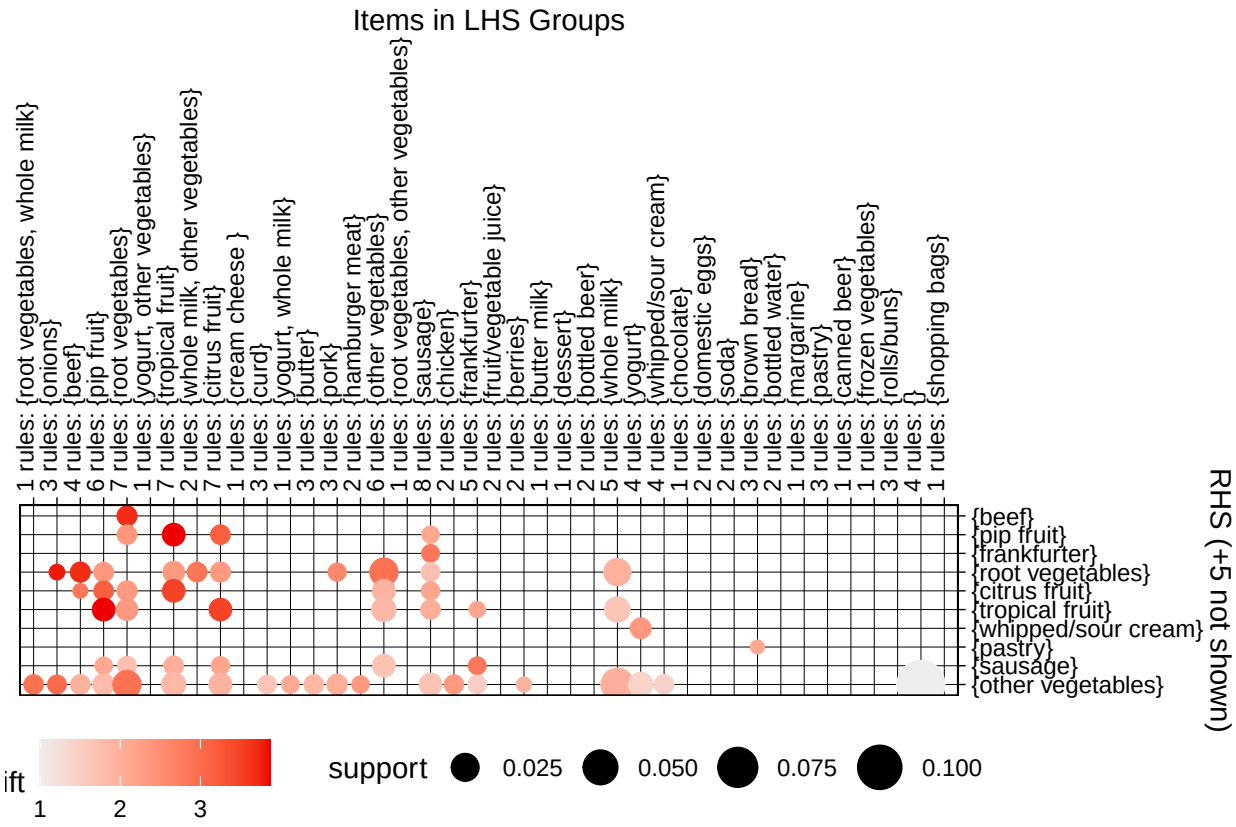
```
##     lhs                                   rhs                support
## [1] {onions}                           => {other vegetables} 0.007452929
## [2] {curd}                             => {whole milk}       0.012617678
## [3] {butter}                           => {whole milk}       0.014382845
## [4] {root vegetables}                  => {other vegetables} 0.025366109
## [5] {root vegetables}                  => {whole milk}       0.022620293
## [6] {other vegetables}                 => {whole milk}       0.040860356
## [7] {other vegetables, root vegetables} => {whole milk}      0.008172071
## [8] {root vegetables, whole milk}      => {other vegetables} 0.008172071
## [9] {other vegetables, yogurt}         => {whole milk}       0.006341527
##     confidence coverage   lift     count
## [1] 0.3737705  0.01993985 3.004306 114
## [2] 0.3683206  0.03425732 2.241875 193
## [3] 0.4036697  0.03563023 2.457036 220
## [4] 0.3619403  0.07008368 2.909216 388
## [5] 0.3227612  0.07008368 1.964566 346
## [6] 0.3284288  0.12441161 1.999064 625
## [7] 0.3221649  0.02536611 1.960937 125
## [8] 0.3612717  0.02262029 2.903842 125
## [9] 0.3991770  0.01588651 2.429690  97
```

```
##      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
```




Scatter plot for 118 rules
confidence
0.4
0.3
0.2
0.1
0.00
0.05
0.10
0.15
support
order
1
2
3



Comments:

First, we had to do some data-wrangling in order to have the data in the correct format to be read. We then plotted the top 10 items in the dataset. After noticing we had a sizable number of each item, we proceeded to set some thresholds for our association rules.

Support: We picked a support of 0.005, because we only wanted to consider itemsets that occurred at least 50 times out of a total of 10,000 transactions in order to be confident that we have enough information to draw a conclusion from our rules.

Confidence: We chose to evaluate items with a confidence level threshold of 0.3. Although this is not extremely high, since confidence can be misleading due to association between items, we chose to have a high lift to make up for this.

Lift: We chose to have a lift threshold of 3, since a high lift means that the rise in probability of having item "Y" in the cart with the knowledge of item "X" being present over the probability of having item "Y" on the cart with no knowledge of item "X" being in the cart. Thus, having a lift of 3 guarantees that there is a strong chance that an individual will purchase item Y if they are already purchasing item "X."

Conclusions: Our association rules make sense, as those who buy meat are likely trying to cook a meal, which requires produce. In addition, people who buy drinks are more likely to purchase other types of drinks available in a grocery store. The importance of each association rule is determined by as high of a lift (the darker the red) and the size of each bubble (the support) shown above. Thus, based on our association rules, we believe that organizing a grocery store would have the best layout by organizing the whole milk next to the vegetables, all non-perishable drinks, such as soda, beer, and water, next to each other (in the same aisle), and with all meat products close to the produce, particularly beef next to citrus fruit.