Excersize 4

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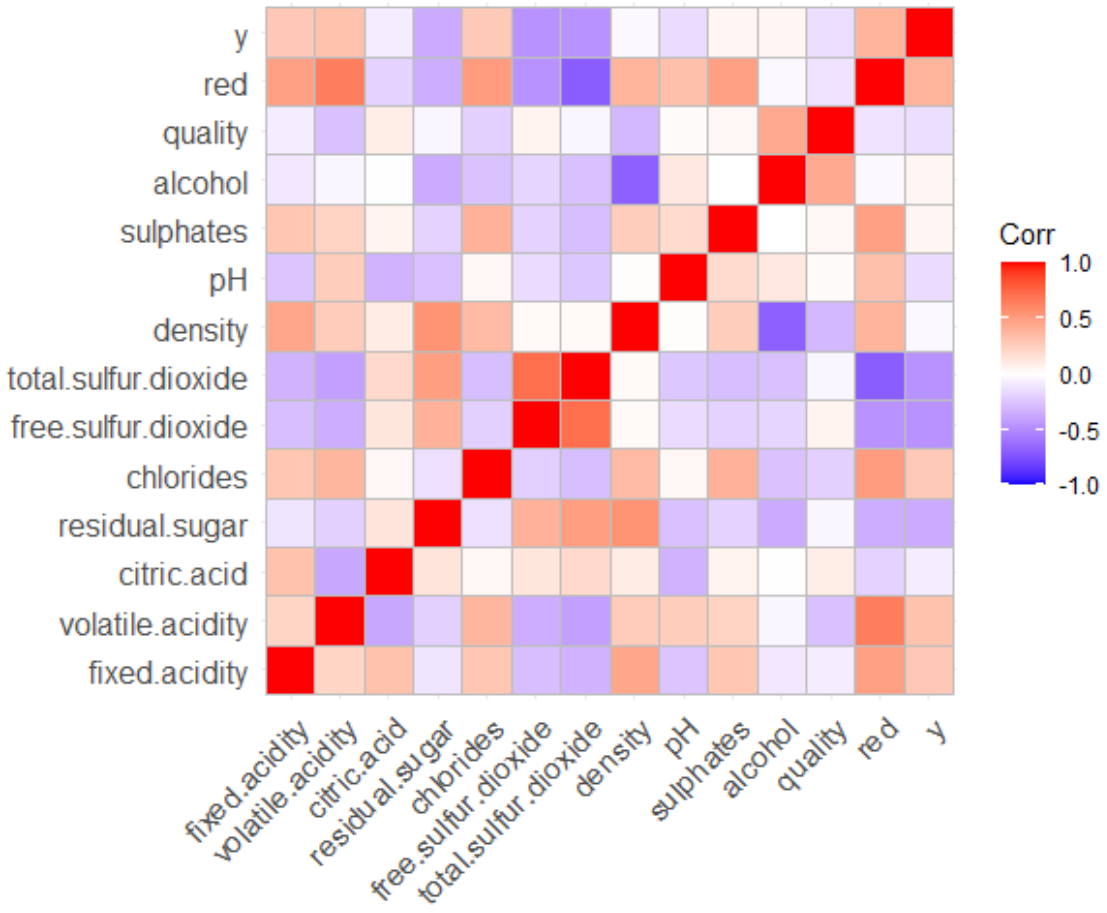
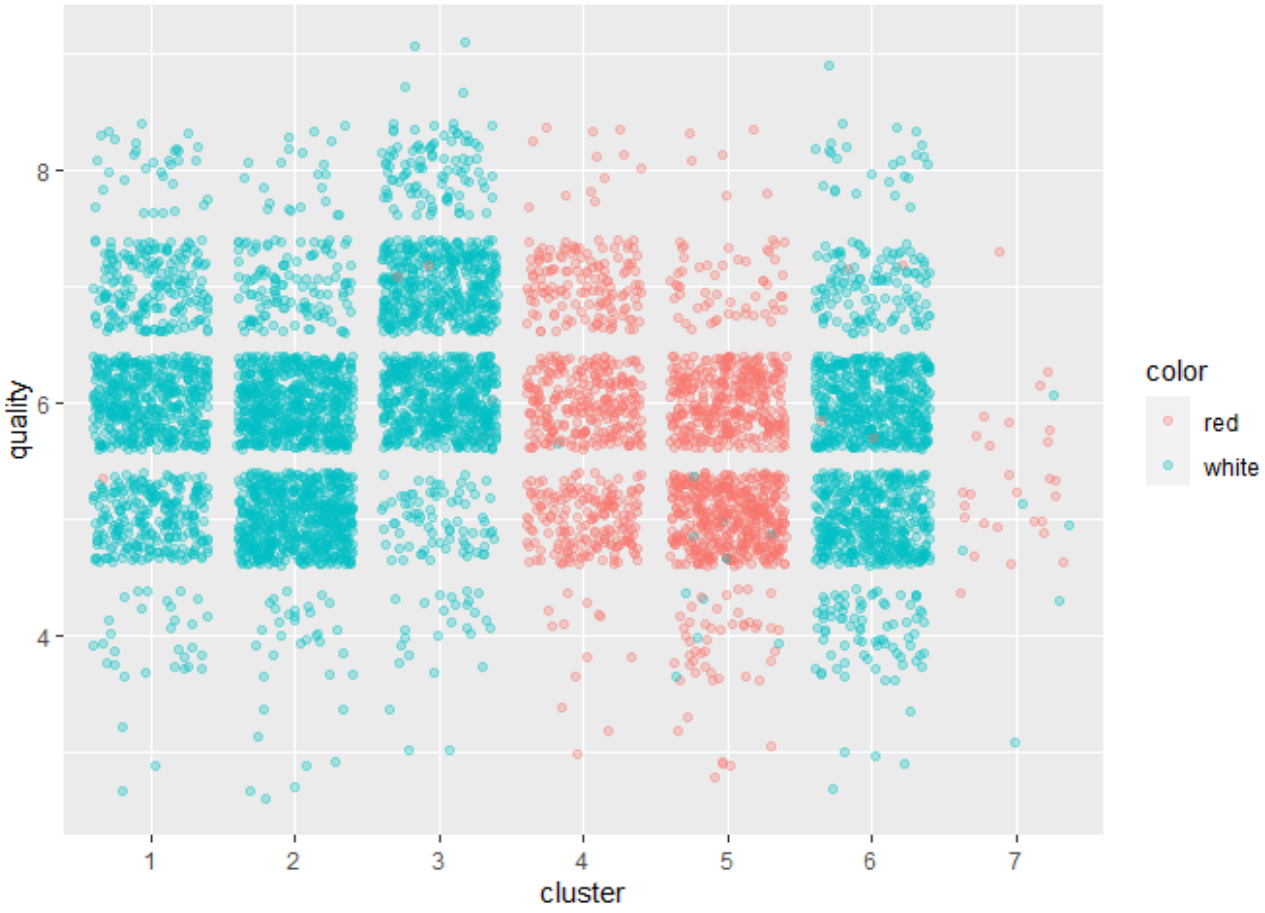
Question 1 - Wine Classification

Clustering Color

cluster	red	white
1	0.0156348	0.9808085
2	0.9843652	0.0191915

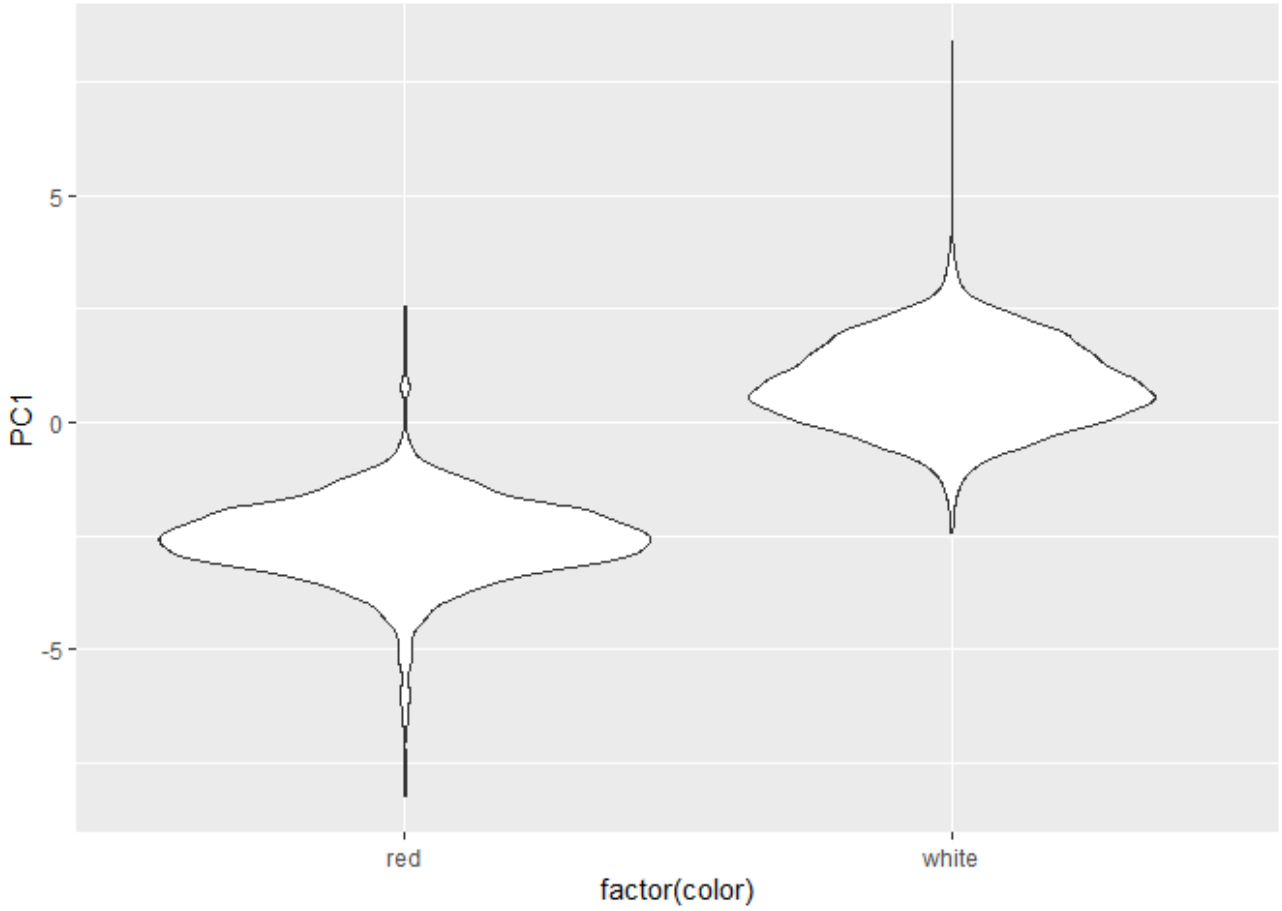
A quick clustering method easily classifies 98% of each wine color, which is hard to beat.


y
red
quality
alcohol
sulphates
pH
density
total.sulfur.dioxide
free.sulfur.dioxide
chlorides
residual.sugar
citric.acid
volatile.acidity
fixed.acidity
fixed.acidity
volatile.acidity
citric.acid
residual.sugar
chlorides
free.sulfur.dioxide
total.sulfur.dioxide
density
pH
sulphates
alcohol
quality
red
y
Corr
1.0
0.5
0.0
-0.5
-1.0


quality
8
6
4
1
2
3
4
5
6
7
cluster
color
red
white

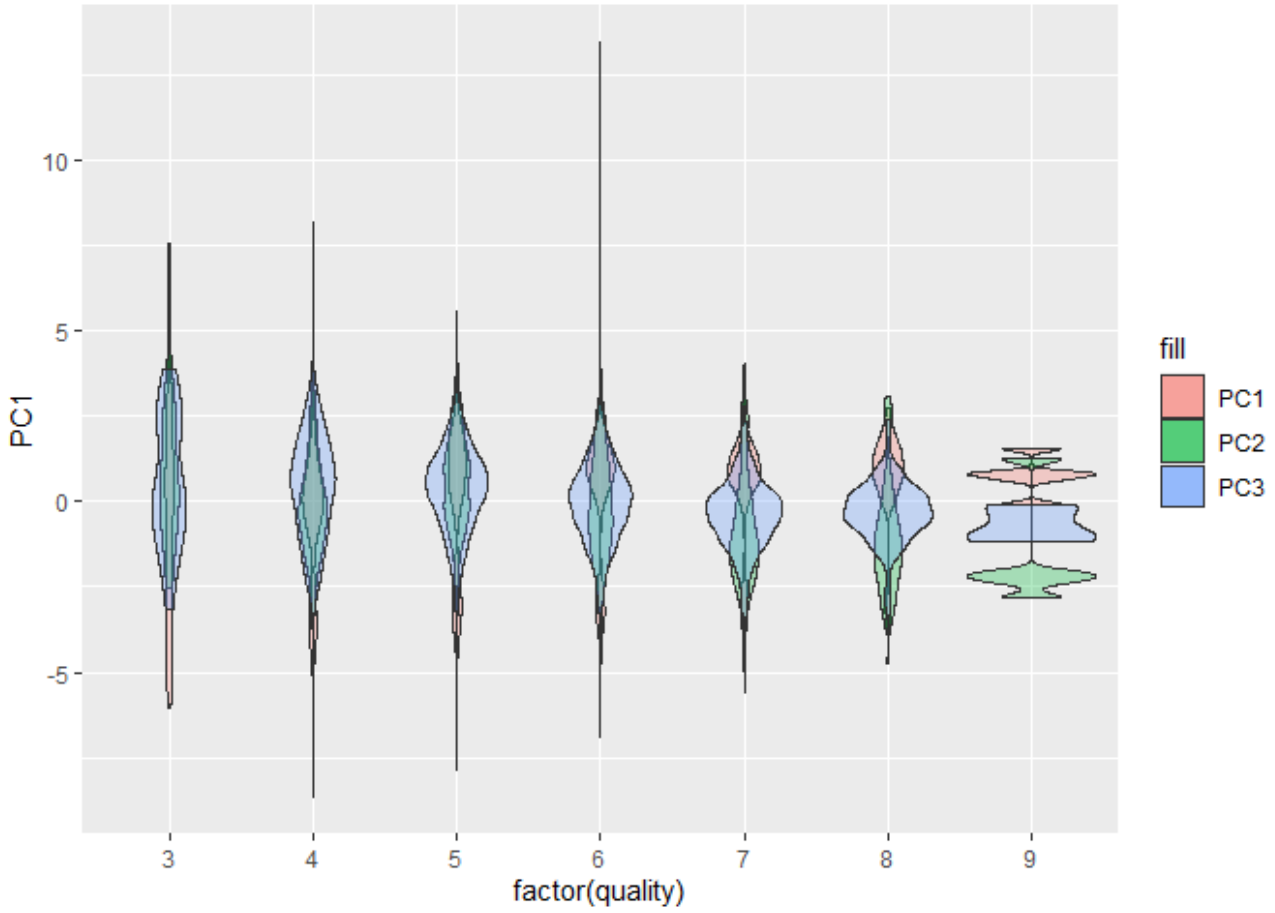
Running clustering algorithm on quality does not yield the same results. The algorithm successfully predicted color but only loosely predicts quality. Notice clusters 1, 2, and 3 which have higher quality concentrations but did not adequately cluster.

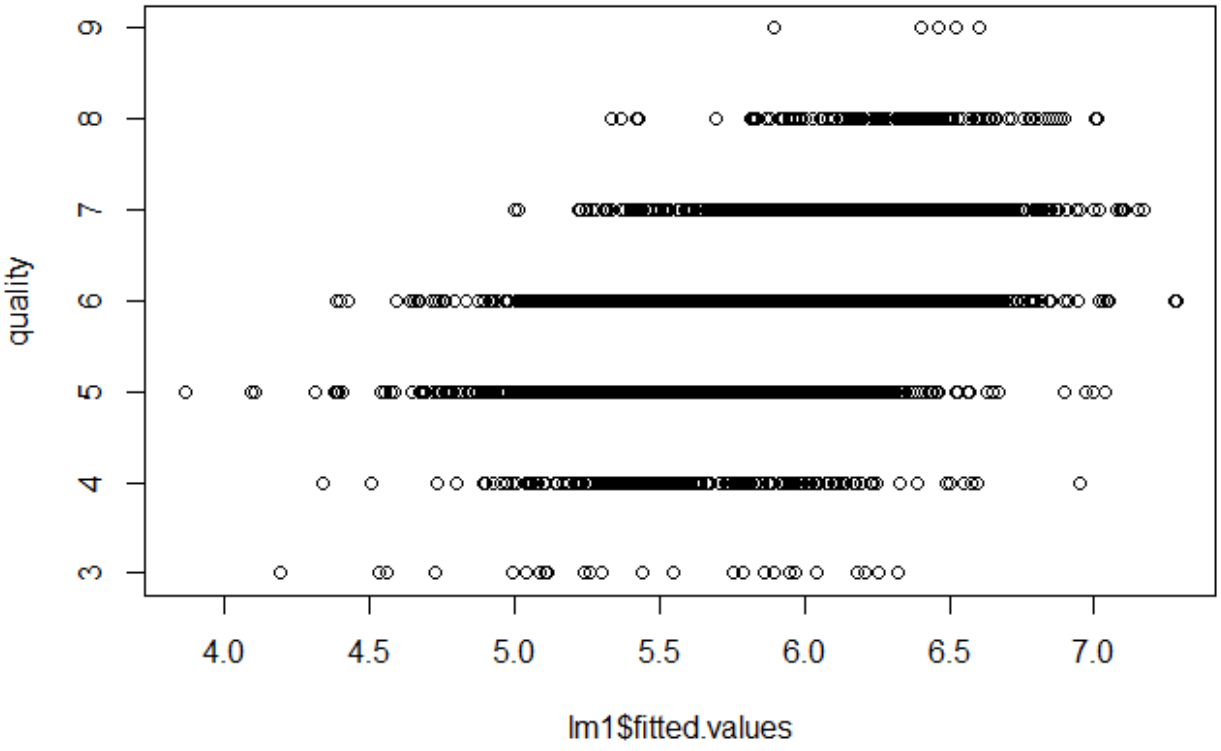
```
## Importance of first k=2 (out of 12) components:
##                           PC1    PC2
## Standard deviation     1.7440 1.6278
## Proportion of Variance 0.2535 0.2208
## Cumulative Proportion  0.2535 0.4743
```



PCA somewhat successfully predicts wine color, but not as well as clustering. This is an artifact of the clustering algorithm's neccesary binning while PCA can have a smoother distribution across factors.

```
## Importance of first k=7 (out of 12) components:
##                           PC1    PC2    PC3    PC4     PC5     PC6    PC7
## Standard deviation     1.9518 1.5902 1.2496 0.9853 0.85077 0.78329 0.7324
## Proportion of Variance 0.3175 0.2107 0.1301 0.0809 0.06032 0.05113 0.0447
## Cumulative Proportion  0.3175 0.5282 0.6583 0.7392 0.79952 0.85065 0.8953
```


PC1
10
5
0
-5
3
4
5
6
7
8
9
factor(quality)
fill
PC1
PC2
PC3

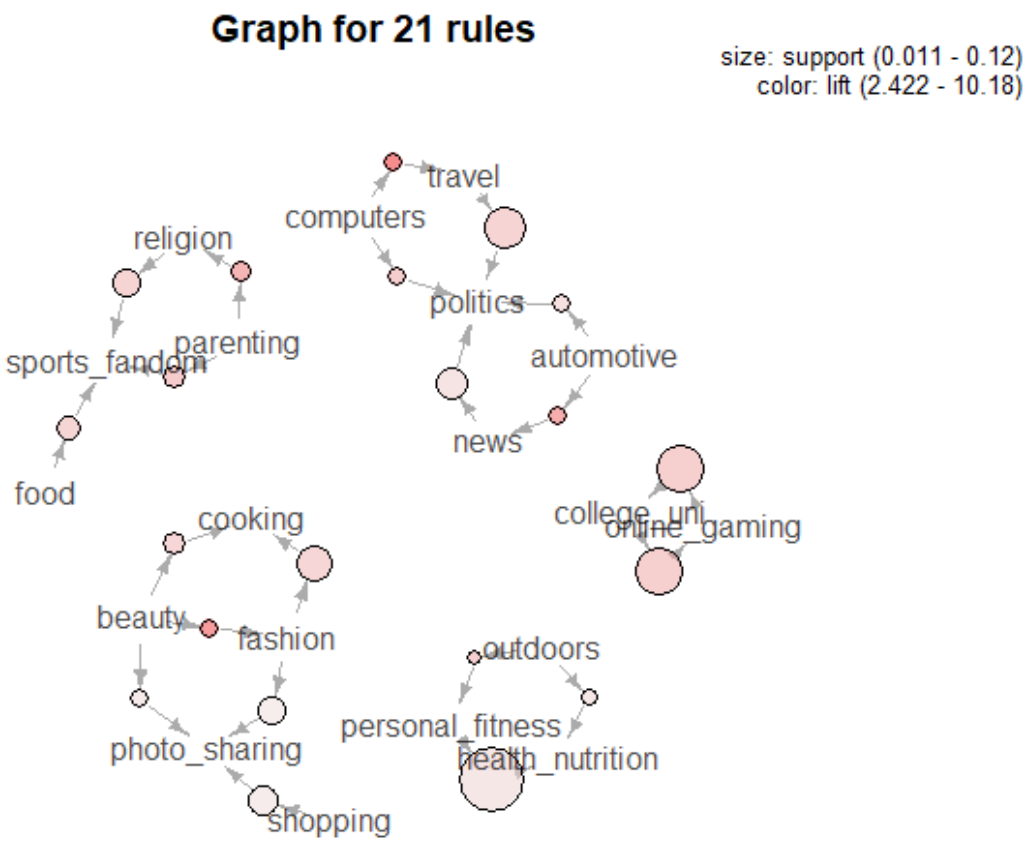

quality
9
8
7
6
5
4
3
4.0
4.5
5.0
5.5
6.0
6.5
7.0
lm1$fitted.values

Running a linear regression on the 7 PCAs, we find that each PC vector slightly predicts quality, but none in particular are selecting for quality, so we would need to introduce an absurd number of PCAs to the system. At that point, we may as well just predict using the features themselves.

Question 2 - Social Marketing

Topic	Count
photo_sharing	21256
health_nutrition	20235
cooking	15750
politics	14098
sports_fandom	12564
travel	12493
college_uni	12213
current_events	12030
personal_fitness	11524
food	11015

From here we see the beginnings of the market structure just by looking at aggregate mentions of each topic, but this is not a detailed marketing strategy.



We removed the “chatter” category because everyone chatters now and then. Instead, we look at the likelihood of people to talk about a topic based on talking about another. The visualization above creates groups based on people’s likely topics of conversation. Though most of these seem intuitive, the clear topic groupings.

The size of each node represents the amount of times it appeared in the data, meaning a higher share of the audience consistently talked about the topic. From this we see multiple clear segments;

1. An outdoorsy, personal health and fitness type consumer, likely to be marketed to via signage and retail placement.
2. An online gaming college student consumer, likely to be marketed to on Twitch and other gaming-oriented social media sites.
3. A beauty, cooking, fashion, and photo sharing consumer, likely marketed to on Instagram.
4. Politics, news, travel, and automotive interested consumer, likely marketed to on Facebook and Twitter.

5. The food, religion, parenting consumer, who may be more difficult to reach in a measured way due to the low relative concentration on any particular digital media. Grocery stores and traditional media would be likely places to build your brand.

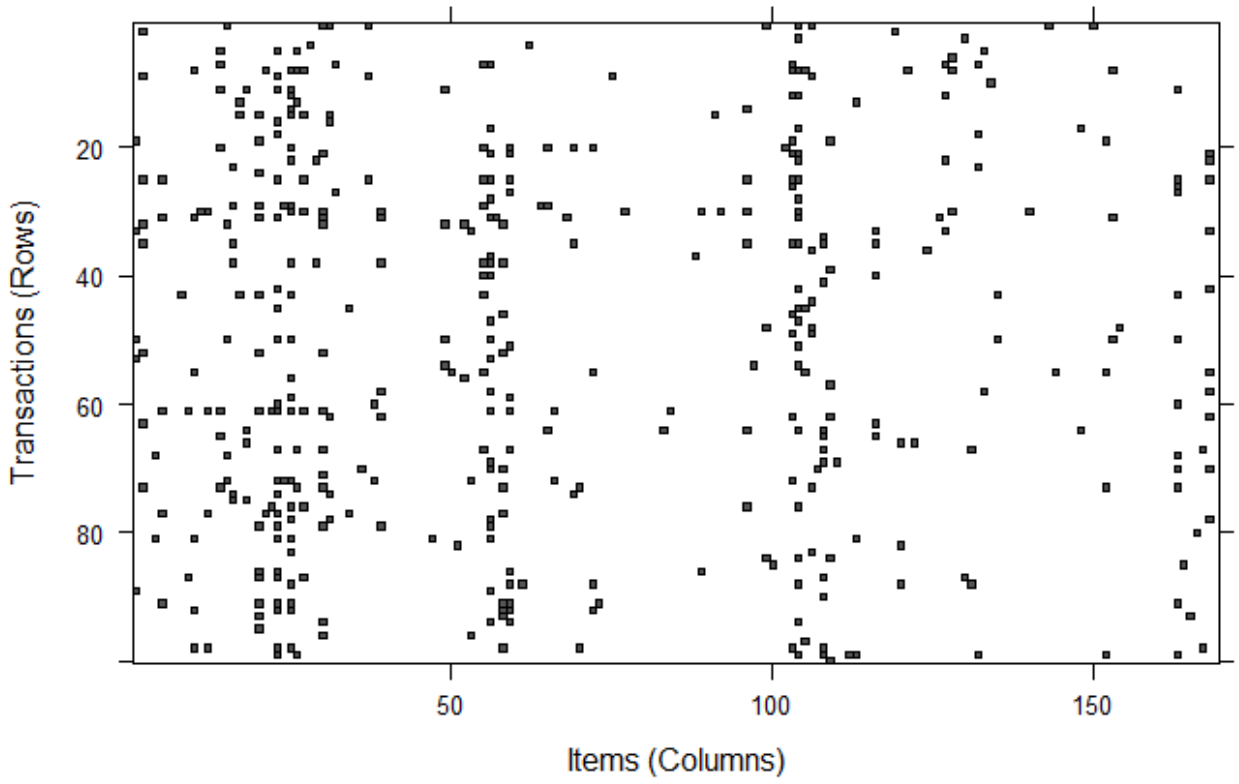
Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster
photo_sharing	college_uni	politics	health_nutrition	sports_
health_nutrition	online_gaming	travel	cooking	religion
current_events	photo_sharing	news	photo_sharing	food
travel	sports_playing	computers	personal_fitness	parenti
shopping	health_nutrition	photo_sharing	fashion	school

Above is the top topics that emerged per-cluster after a completely different algorithm was run against the data. Notice the same pattern emerges under this methodology, emphasizing the natural audiences in the data.

Question 3 - Market Segmentation

First we load the data.

We can examine the sparse matrix of transactions and items in a simple plot.




```
## null device
##           1
```

What are the most frequent item purchases?

```
## Eclat
##
## parameter specification:
##  tidLists support minlen maxlen            target  ext
##     FALSE    0.07      1     15 frequent itemsets TRUE
##
## algorithmic control:
##  sparse sort verbose
##       7   -2    TRUE
##
## Absolute minimum support count: 688
##
## create itemset ...
## set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
## sorting and recoding items ... [18 item(s)] done [0.00s].
## creating sparse bit matrix ... [18 row(s), 9835 column(s)] done [0.00s].
## writing  ... [19 set(s)] done [0.00s].
## Creating S4 object  ... done [0.00s].
```

```
## set of 19 itemsets
##
## most frequent items:
## other vegetables       whole milk          sausage     citrus fruit
##                2                2                1                1
##   tropical fruit          (Other)
##                1               13
##
## element (itemset/transaction) length distribution:sizes
##  1  2
## 18  1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.053   1.000   2.000
##
## summary of quality measures:
##     support        transIdenticalToItemsets     count
##  Min.   :0.07168   Min.   : 705.0           Min.   : 705.0
##  1st Qu.:0.07875   1st Qu.: 774.5           1st Qu.: 774.5
##  Median :0.09395   Median : 924.0           Median : 924.0
##  Mean   :0.11410   Mean   :1122.2           Mean   :1122.2
##  3rd Qu.:0.12501   3rd Qu.:1229.5           3rd Qu.:1229.5
##  Max.   :0.25552   Max.   :2513.0           Max.   :2513.0
##
## includes transaction ID lists: FALSE
##
## mining info:
##       data ntransactions support
##  Groceries          9835    0.07
```

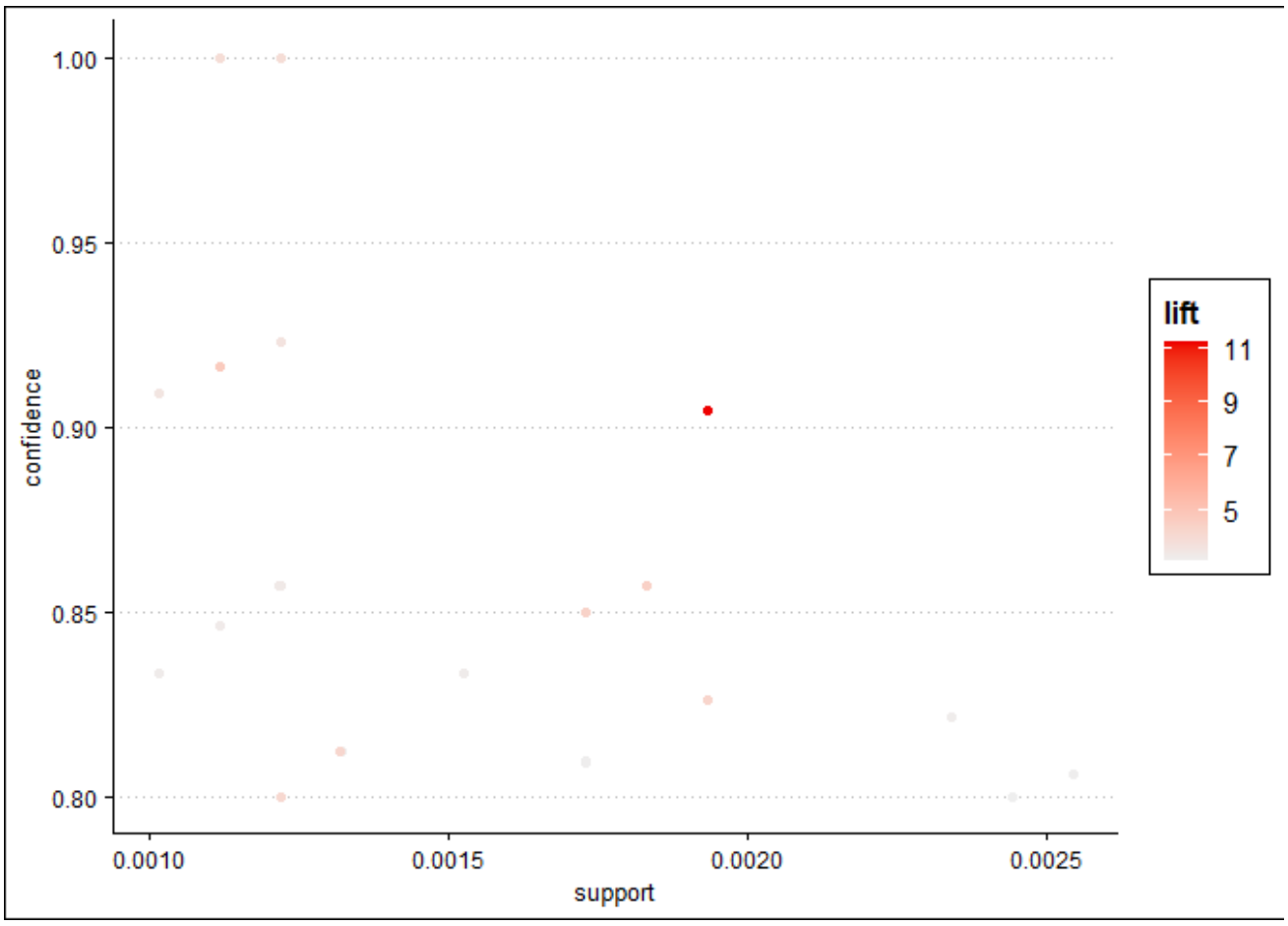
Next, we use the `apriori` function, which implements the Apriori algorithm to mine frequent itemsets, to define rules for purchasing associations.

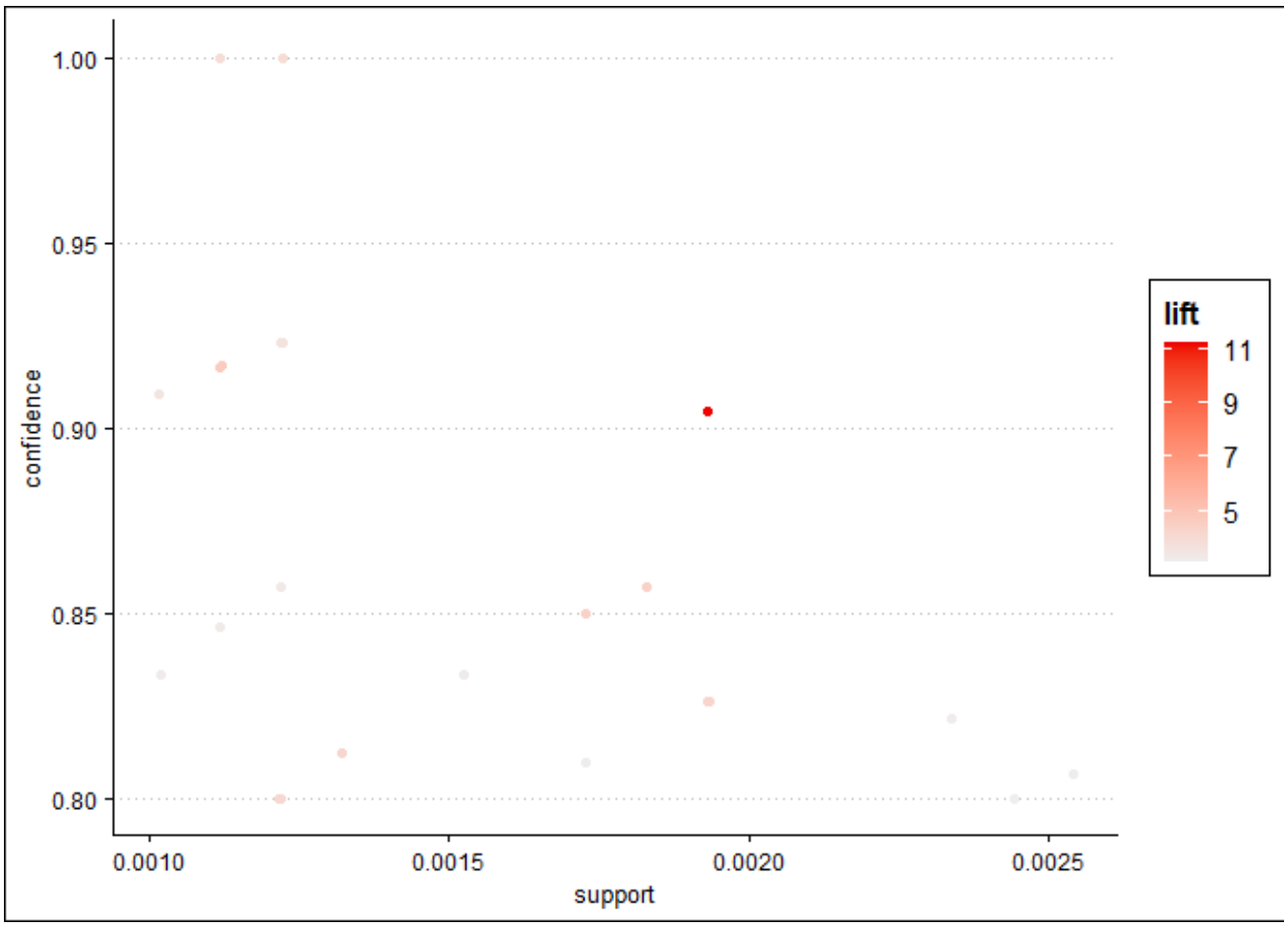
```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##       3  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 9
##
## set item appearances ...[0 item(s)] done [0.00s].
```

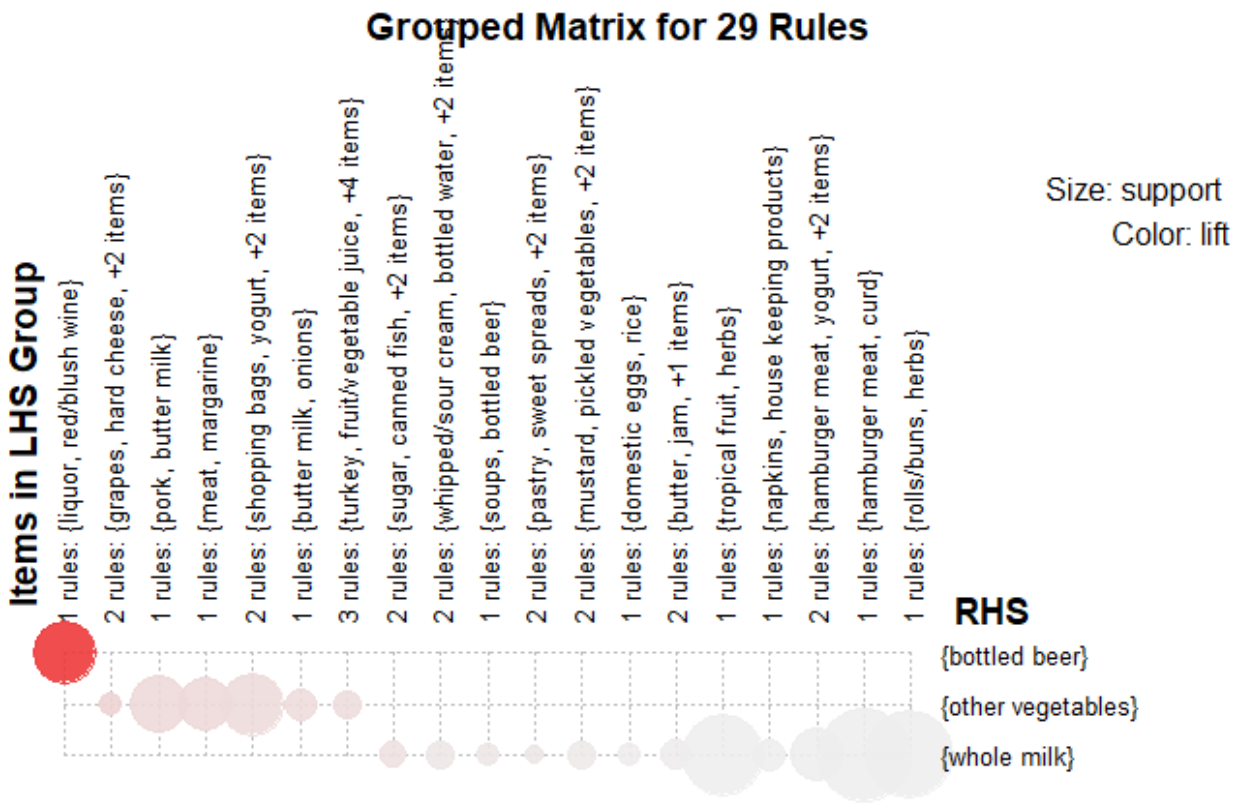
```
## set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
## sorting and recoding items ... [157 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 done [0.00s].
## writing ... [29 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].

## set of 29 rules
##
## rule length distribution (lhs + rhs):sizes
##  3
## 29
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       3       3       3       3       3       3
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001017   Min.   :0.8000   Min.   :0.001118   Min.   : 3.131
##  1st Qu.:0.001118   1st Qu.:0.8125   1st Qu.:0.001220   1st Qu.: 3.261
##  Median :0.001220   Median :0.8462   Median :0.001525   Median : 3.613
##  Mean   :0.001473   Mean   :0.8613   Mean   :0.001732   Mean   : 4.000
##  3rd Qu.:0.001729   3rd Qu.:0.9091   3rd Qu.:0.002135   3rd Qu.: 4.199
##  Max.   :0.002542   Max.   :1.0000   Max.   :0.003152   Max.   :11.235
##      count
##  Min.   :10.00
##  1st Qu.:11.00
##  Median :12.00
##  Mean   :14.48
##  3rd Qu.:17.00
##  Max.   :25.00
##
## mining info:
##       data ntransactions support confidence
##  Groceries          9835   0.001        0.8
```

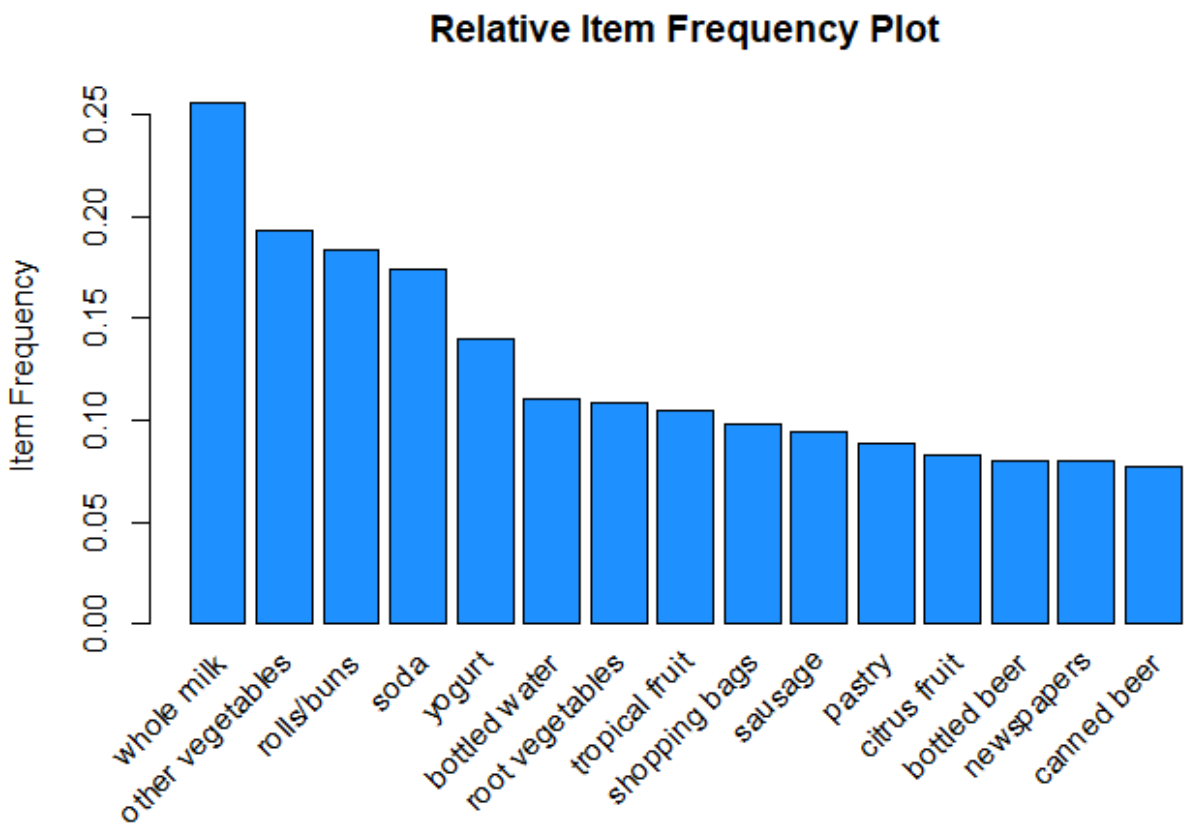
Some of the rules can be visualized.


1.00
0.95
0.90
0.85
0.80
confidence
0.0010
0.0015
0.0020
0.0025
support
lift
11
9
7
5

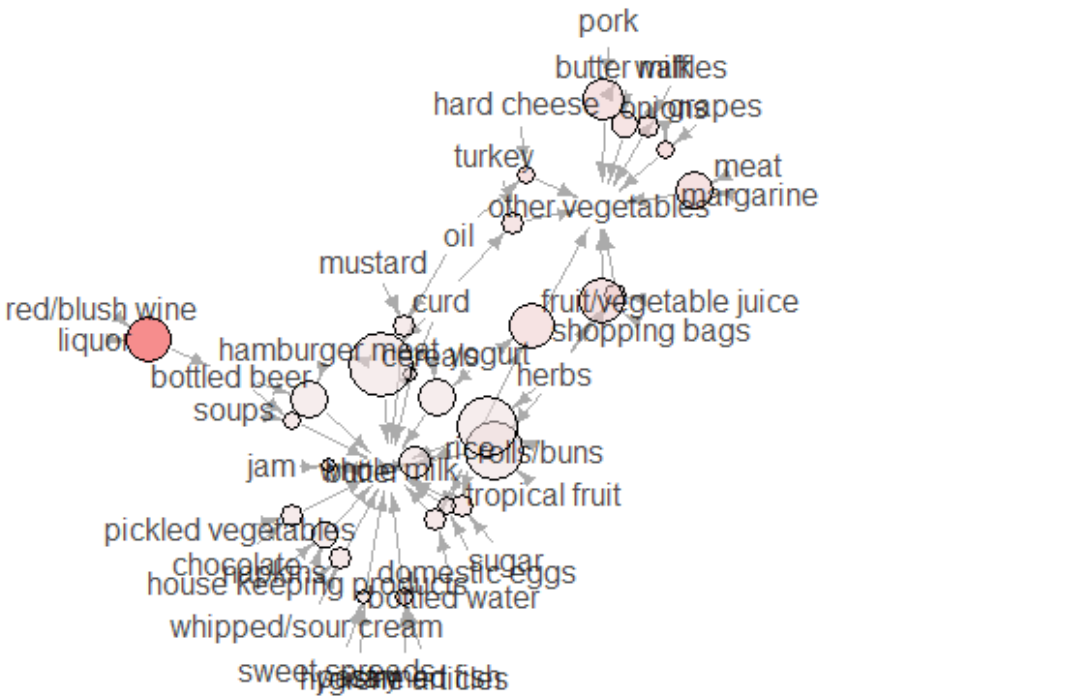

1.00
0.95
0.90
0.85
0.80
confidence
0.0010
0.0015
0.0020
0.0025
support
lift
11
9
7
5



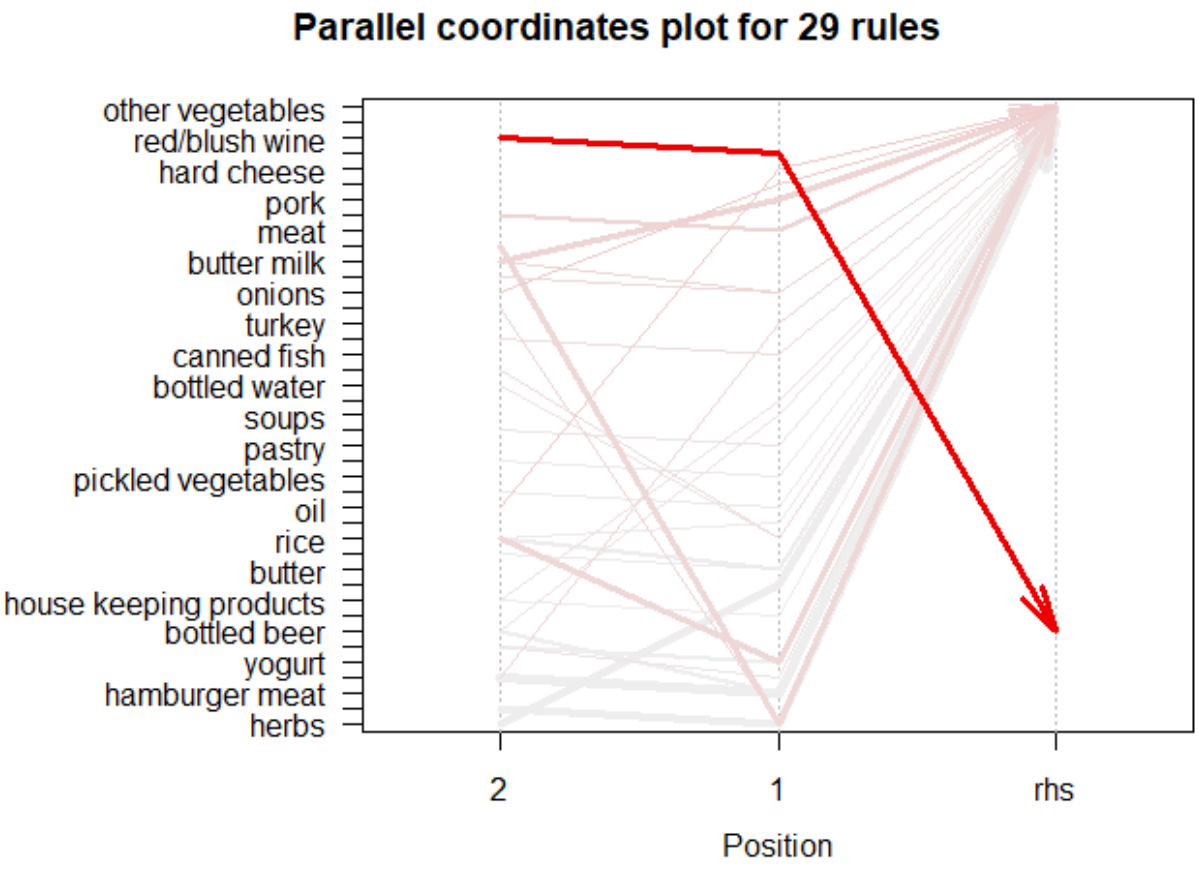
support	confidence	coverage	lift	count
0.0019	0.9048	0.0021	11.2353	19
0.0010	0.9091	0.0011	3.5579	10
0.0017	0.8095	0.0021	3.1682	17
0.0010	0.8333	0.0012	3.2614	10
0.0011	0.9167	0.0012	3.5875	11
0.0013	0.8125	0.0016	3.1798	13




```
## Available control parameters (with default values):
## main  =  Graph for 29 rules
## max   =  100
## nodeCol   =  c("#EE0000FF", "#EE0303FF", "#EE0606FF", "#EE0909FF", "#EE0C0CFF", "#
## itemnodeCol   =  #66CC66FF
## edgeCol   =  #ABABABFF
## labelCol  =  #000000B3
## itemLabels    =  TRUE
## measureLabels     =  FALSE
## precision     =  3
## arrowSize     =  0.5
## alpha     =  0.5
## cex   =  1
## layout    =  NULL
## layoutParams  =  list()
## engine    =  igraph
## plot  =  TRUE
## plot_options  =  list()
## verbose   =  FALSE
```




```
## Available control parameters (with default values):
## main  =  Parallel coordinates plot for 29 rules
## reorder   =  FALSE
## interactive   =  FALSE
## engine    =  default
## gp_labels     =  list()
## newpage   =  TRUE
## col   =  c("#EE0000FF", "#EE0303FF", "#EE0606FF", "#EE0909FF", "#EE0C0CFF", "#EE0F
## alpha     =  NULL
## quality   =  2
## verbose   =  FALSE
```



From the visualizations and the summaries of item pairs, I recommend the following aisles:

1. Groceries Aisle – Milk, Eggs and Vegetables
2. Liquor Aisle – Liquor, Red/Blush Wine, Bottled Beer, Soda
3. Eateries Aisle – Herbs, Tropical Fruits, Rolls/Buns, Fruit Juices, Jams
4. Breakfast Aisle – Cereals, Yogurt, Rice, Curd

Question 4 - Author Attribution

First, we load the data.

Then we pull author names from the file directory and assign them to texts, and do a check to make sure it worked as expected.

Var1	Freq
AaronPressman	50
AlanCrosby	50

Var1	Freq
AlexanderSmith	50
BenjaminKangLim	50
BernardHickey	50
BradDorfman	50
DarrenSchuettler	50
DavidLawder	50
EdnaFernandes	50
EricAuchard	50
FumikoFujisaki	50
GrahamEarnshaw	50
HeatherScoffield	50
JaneMacartney	50
JanLopatka	50
JimGilchrist	50
JoeOrtiz	50
JohnMastrini	50
JonathanBirt	50
JoWinterbottom	50
KarlPenhaul	50
KeithWeir	50
KevinDrawbaugh	50
KevinMorrison	50
KirstinRidley	50
KouroshKarimkhany	50

Var1	Freq
LydiaZajc	50
LynneO’Donnell	50
LynnleyBrowning	50
MarcelMichelson	50
MarkBendeich	50
MartinWolk	50
MatthewBunce	50
MichaelConnor	50
MureDickie	50
NickLouth	50
PatriciaCommins	50
PeterHumphrey	50
PierreTran	50
RobinSidel	50
RogerFillion	50
SamuelPerry	50
SarahDavison	50
ScottHillis	50
SimonCowell	50
TanEeLyn	50
ThieresePoletti	50
TimFarrand	50
ToddNissen	50
WilliamKazer	50

Next, we create the corpus. This is split into a train/test and are stripped of punctuation, forced to lowercase, and numbers are removed — as well as whitespace and common stopwords. I use simple wordclouds to check if this process is working as expected.

To analyze the text, I create document-term matrices from the corpuses.

Finally, with the document-term matrices, I use a naive-bayes classifier to predict the author of the text using a dictionary of words unique to each article.

```
## Naive Bayes Classification
freq_words <- findFreqTerms(train_dtm, 5)
# saving List using Dictionary() Function
Dictionary <- function(x) {
  if (is.character(x)) {
    return(x)
  }
  stop('x is not a character vector')
}
data_dict <- Dictionary(findFreqTerms(train_dtm, 5))
# appending Document Term Matrix to Train and Test Dataset
data_train <- DocumentTermMatrix(train_corpus, list(data_dict))
data_test <- DocumentTermMatrix(test_corpus, list(data_dict))
# converting the frequency of word to count
```

```r
convert_counts <- function(x) {
  x <- ifelse(x > 0, 1, 0)
  x <- factor(x, levels = c(0, 1), labels = c("No", "Yes"))
  return(x)
}
# appending count function to Train and Test Dataset
data_train <- apply(data_train, MARGIN = 2, convert_counts)
data_test <- apply(data_test, MARGIN = 2, convert_counts)
# train model
data_classifier <- naiveBayes(data_train, Data_train$author)
data_test_pred <- predict(data_classifier, data_test)
# CrossTable(data_test_pred, Data_test$author,
#            prop.chisq = FALSE, prop.t = FALSE,
#            dnn = c('predicted', 'actual'))
```

I apply the trained model to the test set and compare the “actual author” to the predicted author.

```
## [1] 0.6724
```

This model guesses correctly (out of 50 authors) 70% of the time.