

# Association Rule Mining

2024-08-18

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr   1.5.1
## v ggplot2    3.5.1      v tibble    3.2.1
## v lubridate  1.9.3      v tidyr     1.3.1
## v purrr      1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(igraph)
```

```
##
## Attaching package: 'igraph'
##
## The following objects are masked from 'package:lubridate':
##
##   %--%, union
##
## The following objects are masked from 'package:dplyr':
##
##   as_data_frame, groups, union
##
## The following objects are masked from 'package:purrr':
##
##   compose, simplify
##
## The following object is masked from 'package:tidyr':
##
##   crossing
##
## The following object is masked from 'package:tibble':
##
##   as_data_frame
##
## The following objects are masked from 'package:stats':
##
##   decompose, spectrum
##
## The following object is masked from 'package:base':
```

```
##  
##      union
```

```
library(arules)
```

```
## Loading required package: Matrix  
##  
## Attaching package: 'Matrix'  
##  
## The following objects are masked from 'package:tidyr':  
##  
##      expand, pack, unpack  
##  
##  
## Attaching package: 'arules'  
##  
## The following object is masked from 'package:dplyr':  
##  
##      recode  
##  
## The following objects are masked from 'package:base':  
##  
##      abbreviate, write
```

```
library(arulesViz)
```

```
grocery_raw = read.csv("/Users/krummelha/Downloads/groceries.txt", header = FALSE)  
  
str(grocery_raw)
```

```
## 'data.frame':  15296 obs. of  4 variables:  
## $ V1: chr  "citrus fruit" "tropical fruit" "whole milk" "pip fruit" ...  
## $ V2: chr  "semi-finished bread" "yogurt" "" "yogurt" ...  
## $ V3: chr  "margarine" "coffee" "" "cream cheese " ...  
## $ V4: chr  "ready soups" "" "" "meat spreads" ...
```

```
summary(grocery_raw)
```

```
##      V1      V2      V3      V4  
## Length:15296 Length:15296 Length:15296 Length:15296  
## Class :character Class :character Class :character Class :character  
## Mode :character Mode :character Mode :character Mode :character
```

```
transactions_list <- split(grocery_raw, seq(nrow(grocery_raw)))  
transactions_list <- lapply(transactions_list, function(x) x[x != ""])
```

```
Groctrans <- as(transactions_list, "transactions")
```

```
summary(Groctrans)
```

```

## 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

```

```

# rules with support > .005 & confidence > .1 & length (# items in cart) <= 3
GroceryRule = apriori(Groctrans,
                      parameter=list(support=.005, confidence=.1, maxlen=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
##      3 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

```

```
## Warning in apriori(Groctrans, parameter = list(support = 0.005, confidence =
## 0.1, : Mining stopped (maxlen reached). Only patterns up to a length of 3
## returned!
```

```
## done [0.00s].
## writing ... [118 rule(s)] done [0.00s].
## creating S4 object ... done [0.00s].
```

```
inspect(GroceryRule)
```

##	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		
## [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
##	[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

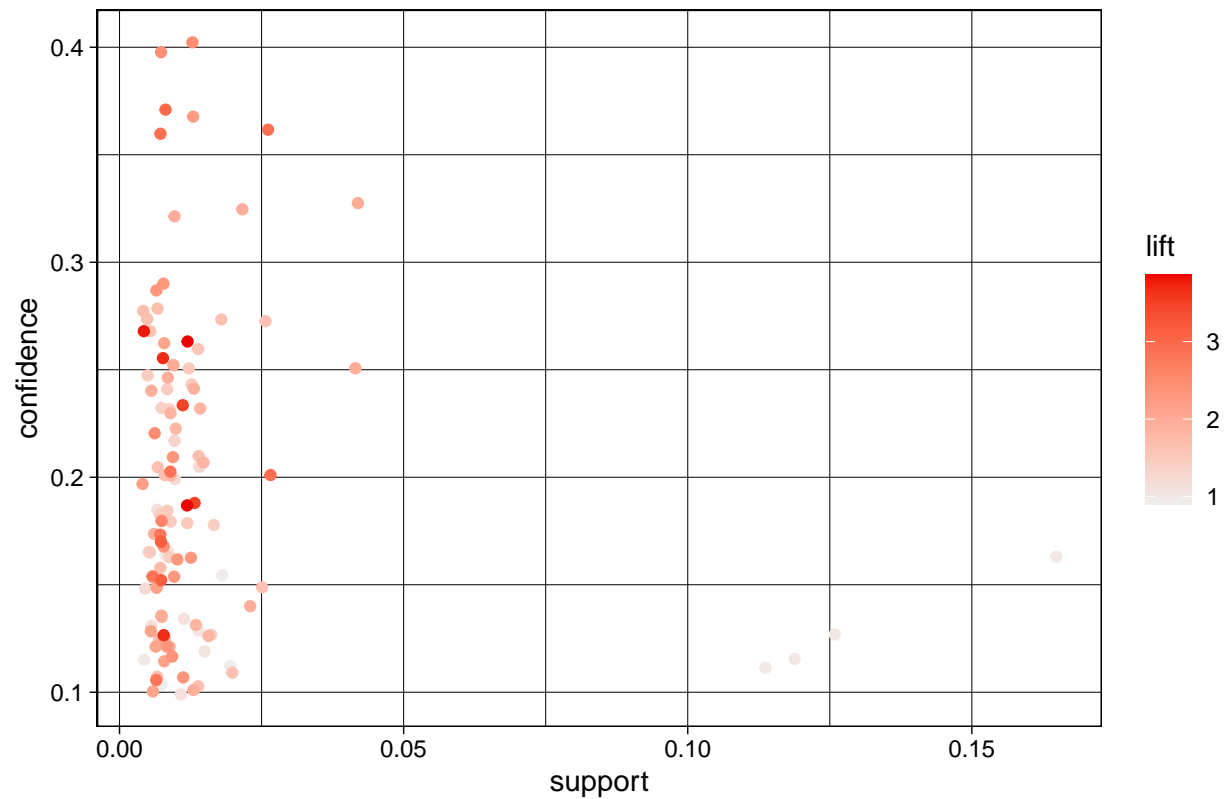
```
## [86] 0.2077922 0.06040795 1.2647790 192
## [87] 0.2060718 0.07106433 1.8379438 224
## [88] 0.1306122 0.11212082 1.8379438 224
## [89] 0.1205152 0.07106433 1.0190161 131
## [90] 0.1627907 0.06746862 2.3228046 168
## [91] 0.1567164 0.07008368 2.3228046 168
## [92] 0.1211240 0.06746862 1.3503740 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
```

```
plot(GroceryRule)
```

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

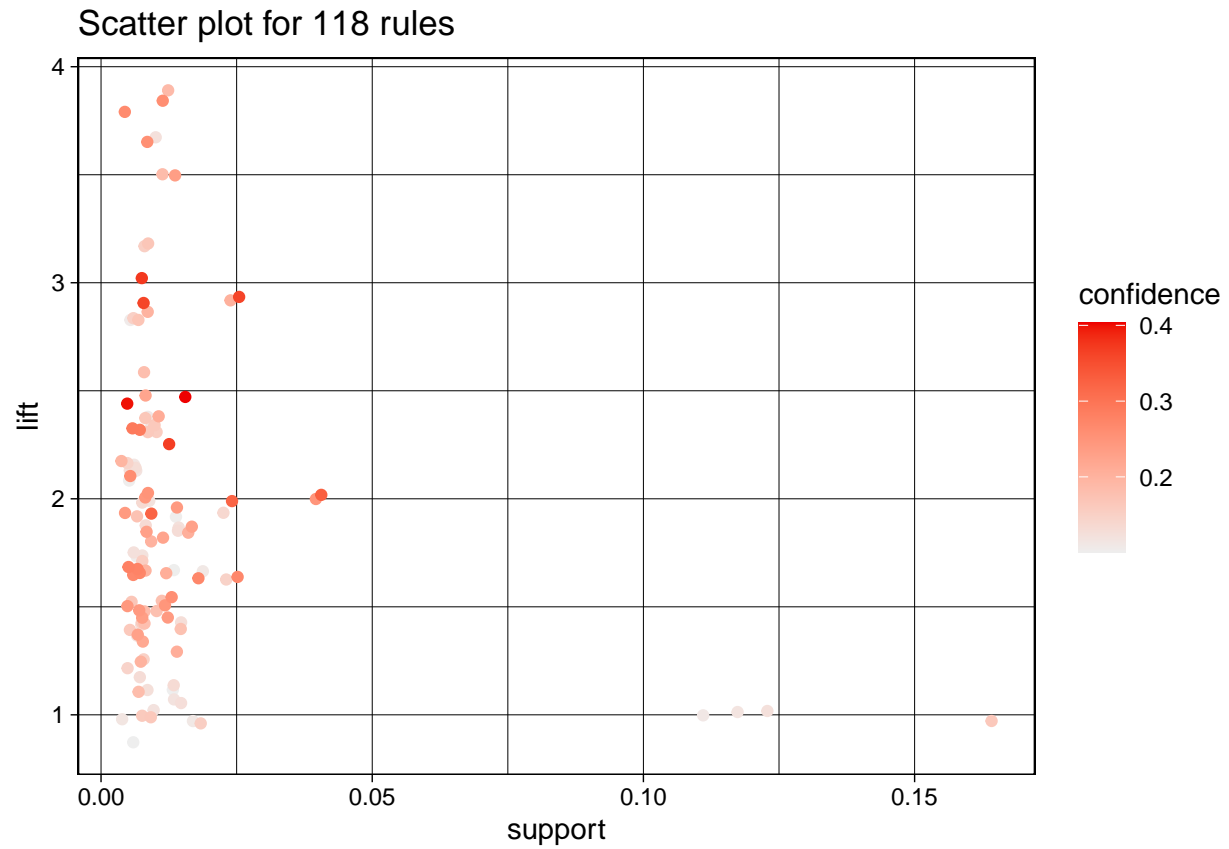


Scatter plot for 118 rules



```
plot(GroceryRule, measure = c("support", "lift"), shading = "confidence")
```

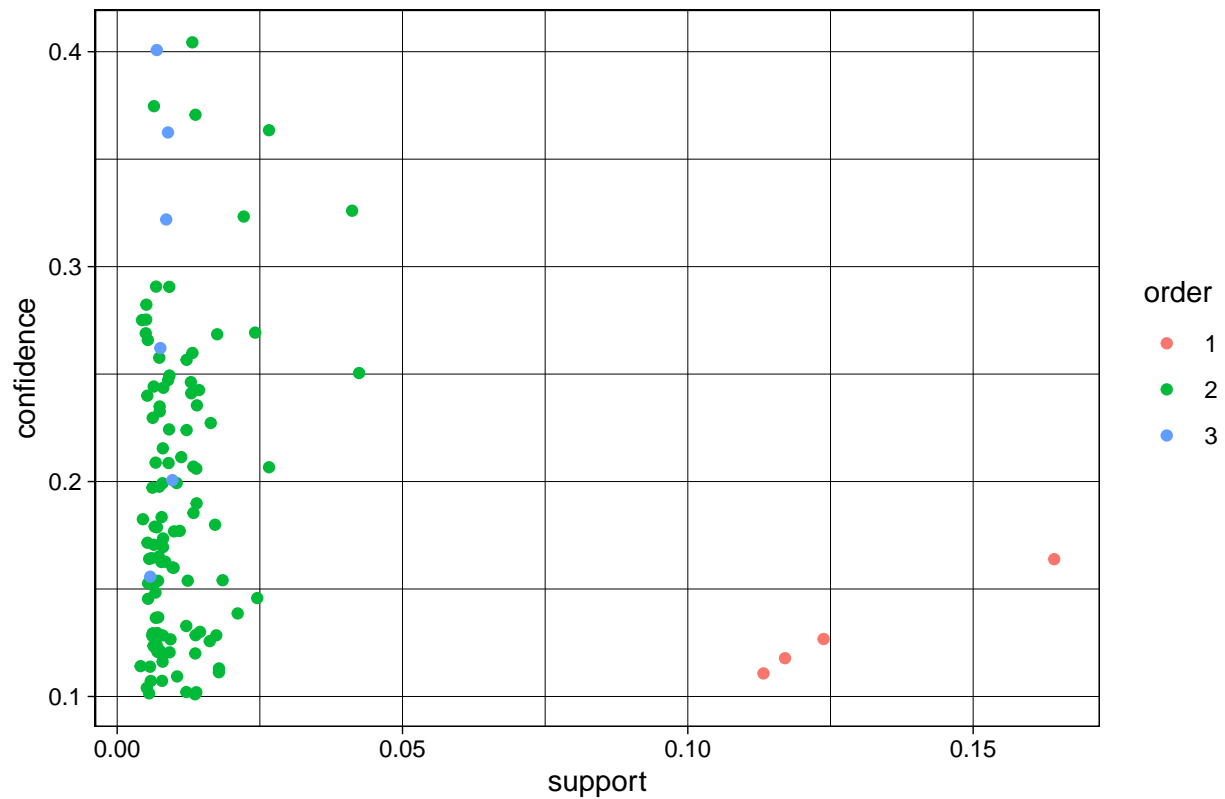
```
## To reduce overplotting, jitter is added! Use jitter = 0 to prevent jitter.
```



```
plot(GroceryRule, method='two-key plot')
```

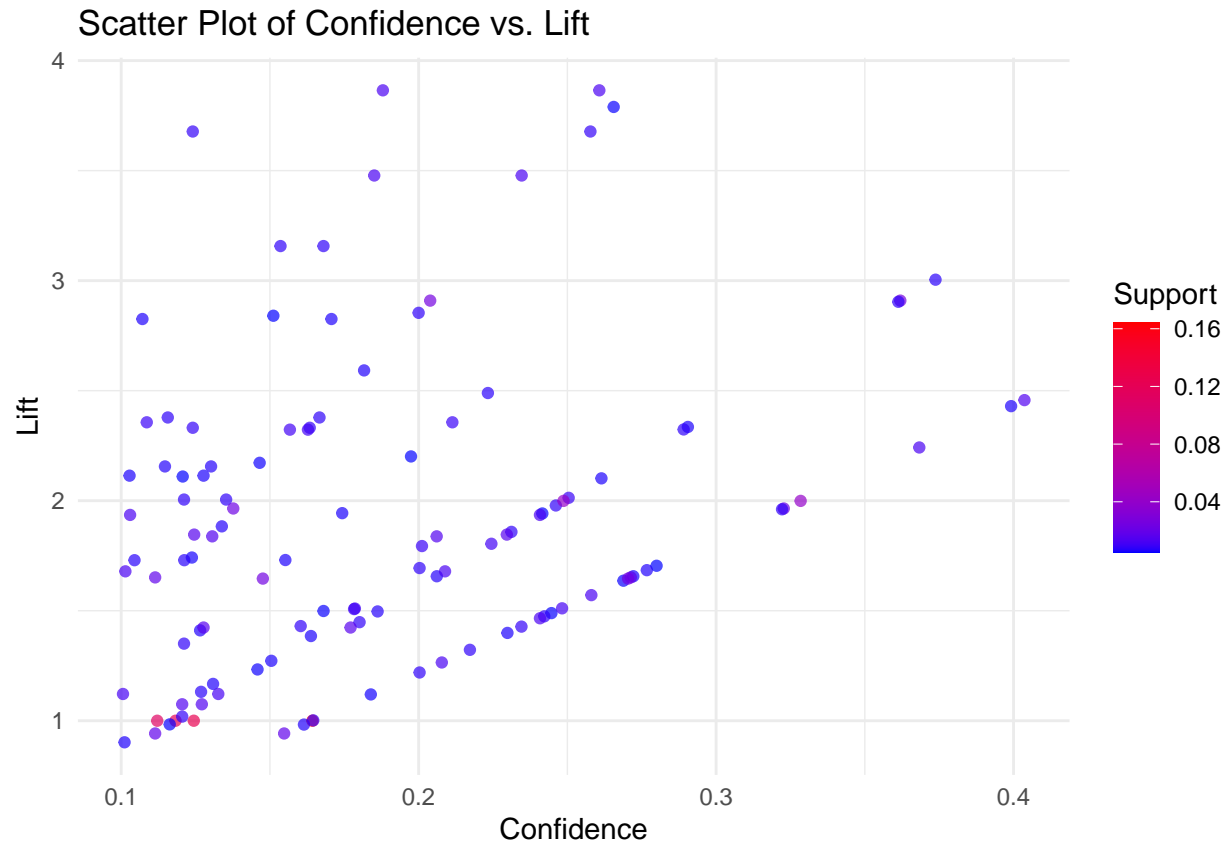
```
## To reduce overplotting, jitter is added! Use jitter = 0 to prevent jitter.
```

Scatter plot for 118 rules



```
# Visualize rule metrics
metrics <- data.frame(
  confidence = quality(GroceryRule)$confidence,
  lift = quality(GroceryRule)$lift,
  support = quality(GroceryRule)$support
)
```

```
# confidence vs. lift with color by support
ggplot(metrics, aes(x = confidence, y = lift, color = support)) +
  geom_point(alpha = 0.7) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(title = "Scatter Plot of Confidence vs. Lift",
       x = "Confidence",
       y = "Lift",
       color = "Support") +
  theme_minimal()
```



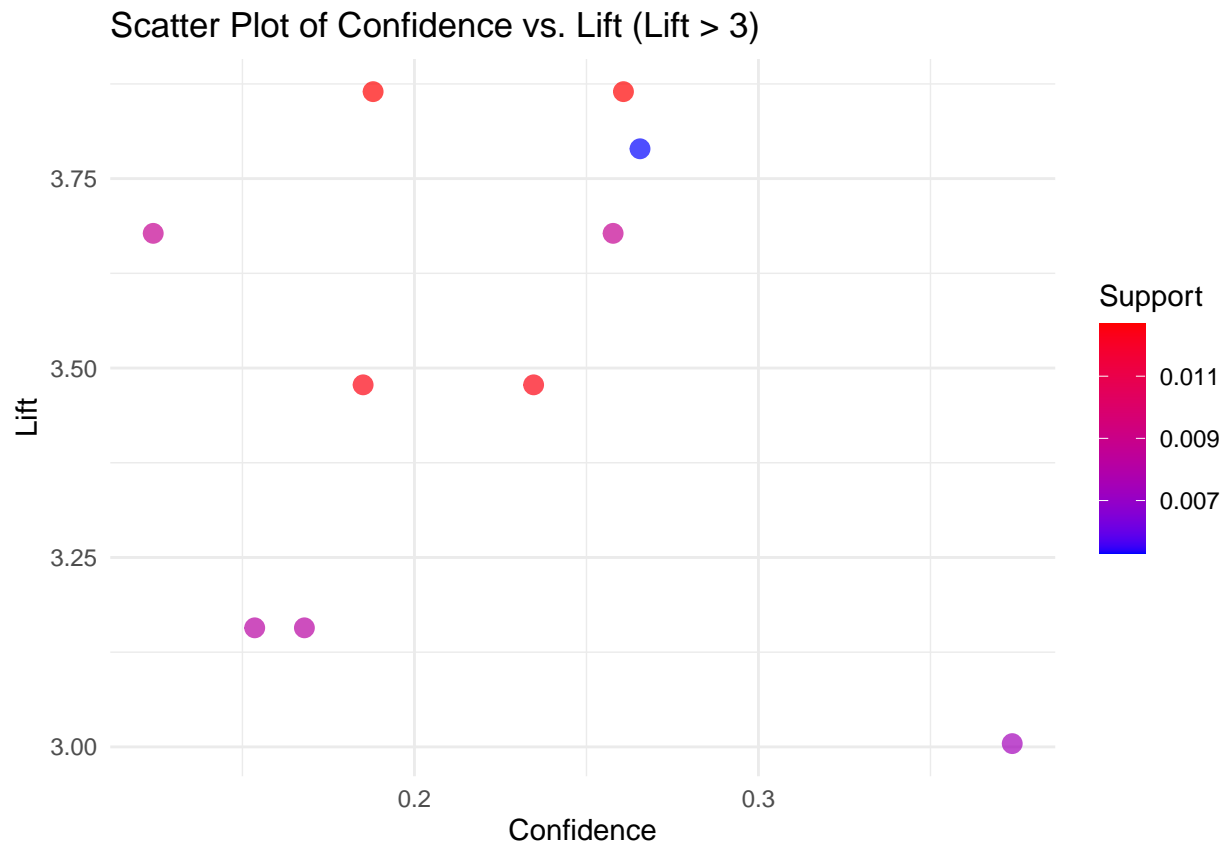
```
# Examine top lifts
inspect(subset(GroceryRule, lift>3))
```

##	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			

```
subset_rules <- subset(GroceryRule, lift > 3)

# Extract metrics from filtered rules
metrics_subset <- data.frame(
  confidence = quality(subset_rules)$confidence,
  lift = quality(subset_rules)$lift,
  support = quality(subset_rules)$support
)

# Scatter plot of confidence vs. lift with color by support
ggplot(metrics_subset, aes(x = confidence, y = lift, color = support)) +
  geom_point(size = 3, alpha = 0.7) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(title = "Scatter Plot of Confidence vs. Lift (Lift > 3)",
       x = "Confidence",
       y = "Lift",
       color = "Support") +
  theme_minimal()
```



Although there are many rows, or shopping carts, in the grocery data, the maximum amount of groceries per single basket in the dataset is 4. It is hard to draw conclusions of associations from that since a lot of items have a low support.

Looking at the plot of lift by confidence, shaded by support, it seems the most confident rules happen at a lift between 2-3, not necessarily at the highest lift (greater than 3).

Some interesting things can be found in the high lift rules. Of those rules that had a lift higher than 3, most

of them were either vegetables or fruit. The combination of these are all complements. One that particularly sticks out is beef and root vegetables. These seem to also be complements of each other. People love stew! Yet, there is no obvious pattern of confidence/lift/support except that they have higher lifts than the rest.

We decided to isolate rules with a lift value greater than or equal to three to focus on those with the highest significance within the dataset. This removed rules which did not provide as much illuminating analysis in the relationships between items bought in this dataset. We chose a support threshold of 0.5%, to minimize the size of our dataset and only focus on the rules and relationships that were the most impactful and insightful. Moreover, we chose a confidence threshold of 10% to minimize our dataset even further and make sure that we understood the most clear lift relationships rather than focus on niche lift rules that may not have offered as much insight.