# ML1000 Assignment 3

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Instacart Market Basket Analysis dataset obtained from https://www.kaggle.com/c/instacart-market-basket-analysis/data (https://www.kaggle.com/c/instacart-market-basket-analysis/data)

The goal of the competition is to predict which products will be in a user's next order.

Read in the merged training data set:

```
X <- read.csv("C:/Users/qt09n/Desktop/Project/orders_TRAIN_products_MERGED.csv")
```

```
str(X)
```

```
## 'data.frame':    1384617 obs. of  16 variables:
##  $ order_id              : num  1 1 1 1 1 1 1 1 36 36 ...
##  $ user_id               : num  112108 112108 112108 112108 112108 ...
##  $ eval_set              : chr  "train" "train" "train" "train" ...
##  $ order_number          : int  4 4 4 4 4 4 4 4 23 23 ...
##  $ order_dow             : int  4 4 4 4 4 4 4 4 6 6 ...
##  $ order_hour_of_day     : int  10 10 10 10 10 10 10 10 18 18 ...
##  $ days_since_prior_order: int  9 9 9 9 9 9 9 9 30 30 ...
##  $ product_id            : int  10246 11109 22035 47209 13176 49302 49683 43633 39612 46620 ...
##  $ add_to_cart_order     : int  3 2 8 7 6 1 4 5 1 5 ...
##  $ reordered             : int  0 1 1 0 0 1 0 1 0 1 ...
##  $ product_name          : chr  "Organic Celery Hearts" "Organic 4% Milk Fat Whole Milk Cottage Chees
##  $ aisle                 : chr  "fresh vegetables" "other creams cheeses" "packaged cheese" "fresh fi
##  $ department            : chr  "produce" "dairy eggs" "dairy eggs" "produce" ...
##  $ aisle_id              : int  83 108 21 24 24 120 83 95 2 86 ...
##  $ department_id         : int  4 16 16 4 4 16 4 15 16 16 ...
##  $ X_merge               : int  3 3 3 3 3 3 3 3 3 3 ...
```

Check missing values: complete.cases will return a logical vector indicating which rows have no missing values. Then use the vector to get only complete rows with X[,]

```
X <- X[complete.cases(X),]
```

look at first 10 rows of dataset

```
head(X)
```

```
##   order_id user_id eval_set order_number order_dow order_hour_of_day
## 1        1  112108    train            4         4                10
```

```
## 2        1  112108    train           4         4                10
## 3        1  112108    train           4         4                10
## 4        1  112108    train           4         4                10
## 5        1  112108    train           4         4                10
## 6        1  112108    train           4         4                10
##   days_since_prior_order product_id add_to_cart_order reordered
## 1                      9      10246                 3         0
## 2                      9      11109                 2         1
## 3                      9      22035                 8         1
## 4                      9      47209                 7         0
## 5                      9      13176                 6         0
## 6                      9      49302                 1         1
##                                product_name               aisle department
## 1                      Organic Celery Hearts     fresh vegetables    produce
## 2 Organic 4% Milk Fat Whole Milk Cottage Cheese other creams cheeses dairy eggs
## 3                   Organic Whole String Cheese      packaged cheese dairy eggs
## 4                         Organic Hass Avocado         fresh fruits    produce
## 5                        Bag of Organic Bananas         fresh fruits    produce
## 6                             Bulgarian Yogurt               yogurt dairy eggs
##   aisle_id department_id X_merge
## 1       83             4       3
## 2      108            16       3
## 3       21            16       3
## 4       24             4       3
## 5       24             4       3
## 6      120            16       3
```

```
summary(X)
```

```
##     order_id          user_id         eval_set          order_number
##  Min.   :      1   Min.   :     1   Length:1384617     Min.   :  4.00
##  1st Qu.: 843370   1st Qu.: 51732   Class :character   1st Qu.:  6.00
##  Median :1701880   Median :102933   Mode  :character   Median : 11.00
##  Mean   :1706298   Mean   :103113                      Mean   : 17.09
##  3rd Qu.:2568023   3rd Qu.:154959                      3rd Qu.: 21.00
##  Max.   :3421070   Max.   :206209                      Max.   :100.00
##    order_dow     order_hour_of_day days_since_prior_order   product_id
##  Min.   :0.000   Min.   : 0.00     Min.   : 0.00          Min.   :    1
##  1st Qu.:1.000   1st Qu.:10.00     1st Qu.: 7.00          1st Qu.:13380
##  Median :3.000   Median :14.00     Median :15.00          Median :25298
##  Mean   :2.701   Mean   :13.58     Mean   :17.07          Mean   :25556
##  3rd Qu.:5.000   3rd Qu.:17.00     3rd Qu.:30.00          3rd Qu.:37940
##  Max.   :6.000   Max.   :23.00     Max.   :30.00          Max.   :49688
##  add_to_cart_order   reordered      product_name          aisle
##  Min.   : 1.000    Min.   :0.0000   Length:1384617     Length:1384617
##  1st Qu.: 3.000    1st Qu.:0.0000   Class :character   Class :character
##  Median : 7.000    Median :1.0000   Mode  :character   Mode  :character
##  Mean   : 8.758    Mean   :0.5986
##  3rd Qu.:12.000    3rd Qu.:1.0000
##  Max.   :80.000    Max.   :1.0000
##   department           aisle_id     department_id      X_merge
##  Length:1384617     Min.   :  1.0   Min.   : 1.00   Min.   :3
##  Class :character   1st Qu.: 31.0   1st Qu.: 4.00   1st Qu.:3
##  Mode  :character   Median : 83.0   Median : 8.00   Median :3
```

```
##                     Mean   : 71.3   Mean   : 9.84   Mean   :3
##                     3rd Qu.:107.0   3rd Qu.:16.00   3rd Qu.:3
##                     Max.   :134.0   Max.   :21.00   Max.   :3
```

Change the character columns to factors and create a new column using mutate:

```
X$product_name <- as.factor(X$product_name)
X$department<- as.factor(X$department)
X$aisle <- as.factor(X$aisle)
```

```
unique(X$aisle)
```

```
##   [1] fresh vegetables              other creams cheeses
##   [3] packaged cheese               fresh fruits
##   [5] yogurt                        canned meat seafood
##   [7] specialty cheeses             eggs
##   [9] lunch meat                    cream
##  [11] water seltzer sparkling water packaged vegetables fruits
##  [13] oils vinegars                 fresh herbs
##  [15] frozen produce                nuts seeds dried fruit
##  [17] canned meals beans            food storage
##  [19] baking ingredients            hot dogs bacon sausage
##  [21] refrigerated                  plates bowls cups flatware
##  [23] butter                        canned jarred vegetables
##  [25] paper goods                   fresh dips tapenades
##  [27] soup broth bouillon           dish detergents
##  [29] tortillas flat bread          condiments
##  [31] milk                          soap
##  [33] frozen meat seafood           soy lactosefree
##  [35] canned fruit applesauce       refrigerated pudding desserts
##  [37] laundry                       frozen appetizers sides
##  [39] crackers                      ice cream ice
##  [41] juice nectars                 chips pretzels
##  [43] cold flu allergy              muscles joints pain relief
##  [45] pasta sauce                   bread
##  [47] grains rice dried goods       spreads
##  [49] popcorn jerky                 baby accessories
##  [51] other                         missing
##  [53] digestion                     more household
##  [55] packaged produce              breakfast bars pastries
##  [57] candy chocolate               spices seasonings
##  [59] cleaning products             diapers wipes
##  [61] fresh pasta                   frozen breakfast
##  [63] asian foods                   preserved dips spreads
##  [65] latino foods                  pickled goods olives
##  [67] instant foods                 energy granola bars
##  [69] packaged meat                 hot cereal pancake mixes
##  [71] soft drinks                   cookies cakes
##  [73] frozen pizza                  tea
##  [75] prepared meals                energy sports drinks
##  [77] poultry counter               trail mix snack mix
##  [79] doughs gelatins bake mixes    prepared soups salads
##  [81] buns rolls                    dry pasta
```

```
##  [83] deodorants                   cereal
##  [85] frozen meals                 breakfast bakery
##  [87] white wines                  coffee
##  [89] fruit vegetable snacks       oral hygiene
##  [91] packaged seafood             bulk grains rice dried goods
##  [93] packaged poultry             body lotions soap
##  [95] tofu meat alternatives       dog food care
##  [97] bakery desserts              baby food formula
##  [99] honeys syrups nectars        meat counter
## [101] trash bags liners            kitchen supplies
## [103] hair care                    beers coolers
## [105] first aid                    vitamins supplements
## [107] granola                      protein meal replacements
## [109] shave needs                  salad dressing toppings
## [111] indian foods                 frozen vegan vegetarian
## [113] spirits                      frozen dessert
## [115] mint gum                     cat food care
## [117] facial care                  specialty wines champagnes
## [119] skin care                    frozen breads doughs
## [121] red wines                    marinades meat preparation
## [123] feminine care                baking supplies decor
## [125] ice cream toppings           seafood counter
## [127] cocoa drink mixes            kosher foods
## [129] air fresheners candles       beauty
## [131] bulk dried fruits vegetables eye ear care
## [133] baby bath body care          frozen juice
## 134 Levels: air fresheners candles asian foods ... yogurt
```

```
#134 aisles
```

```
unique(X$department)
```

```
##  [1] produce         dairy eggs      canned goods    deli
##  [5] beverages       pantry          frozen          snacks
##  [9] household       meat seafood    bakery          personal care
## [13] dry goods pasta babies          other           missing
## [17] breakfast       international   alcohol         bulk
## [21] pets
## 21 Levels: alcohol babies bakery beverages breakfast bulk ... snacks
```

```
levels(X$department)
```

```
##  [1] "alcohol"         "babies"          "bakery"          "beverages"
##  [5] "breakfast"       "bulk"            "canned goods"    "dairy eggs"
##  [9] "deli"            "dry goods pasta" "frozen"          "household"
## [13] "international"   "meat seafood"    "missing"         "other"
## [17] "pantry"          "personal care"   "pets"            "produce"
## [21] "snacks"
```

```
#21 departments
```

```
length(unique(X$product_name))
```

```
## [1] 39123
```

```
#39123 products
```

```
class(X$order_hour_of_day)
```

```
## [1] "integer"
```

```
#[1] "integer"
```

How many unique orders are in the training dataset?

```
length(unique(X$order_id))
```

```
## [1] 131209
```

How many users are in the training dataset?

```
length(unique(X$user_id))
```

```
## [1] 131209
```

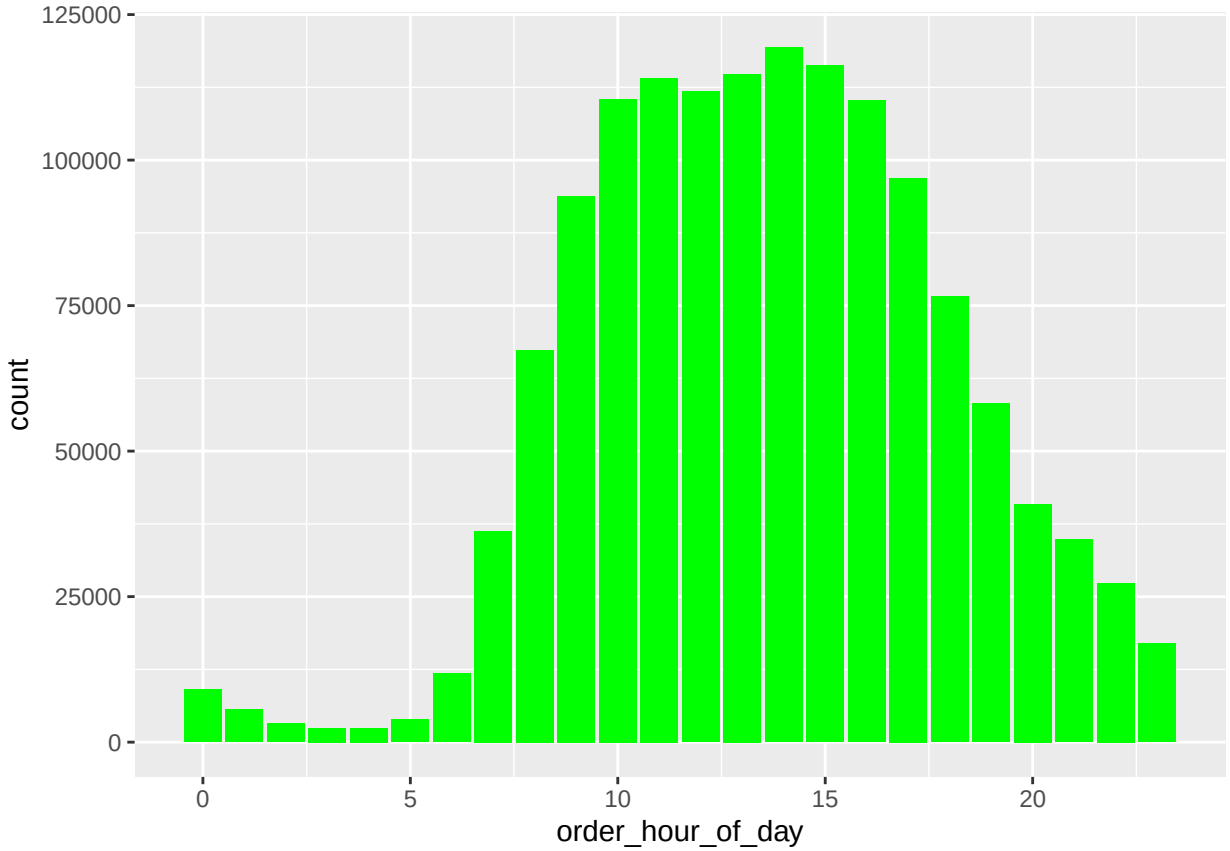
So it looks like the number of users are the same as the number of orders...

Recode order_hour_of_day to numeric:

```
X$order_hour_of_day <- as.numeric(X$order_hour_of_day)
```

Look at when people order:

```
X %>% ggplot(aes(x= order_hour_of_day)) +
  geom_bar(stat="count", fill="green")
```

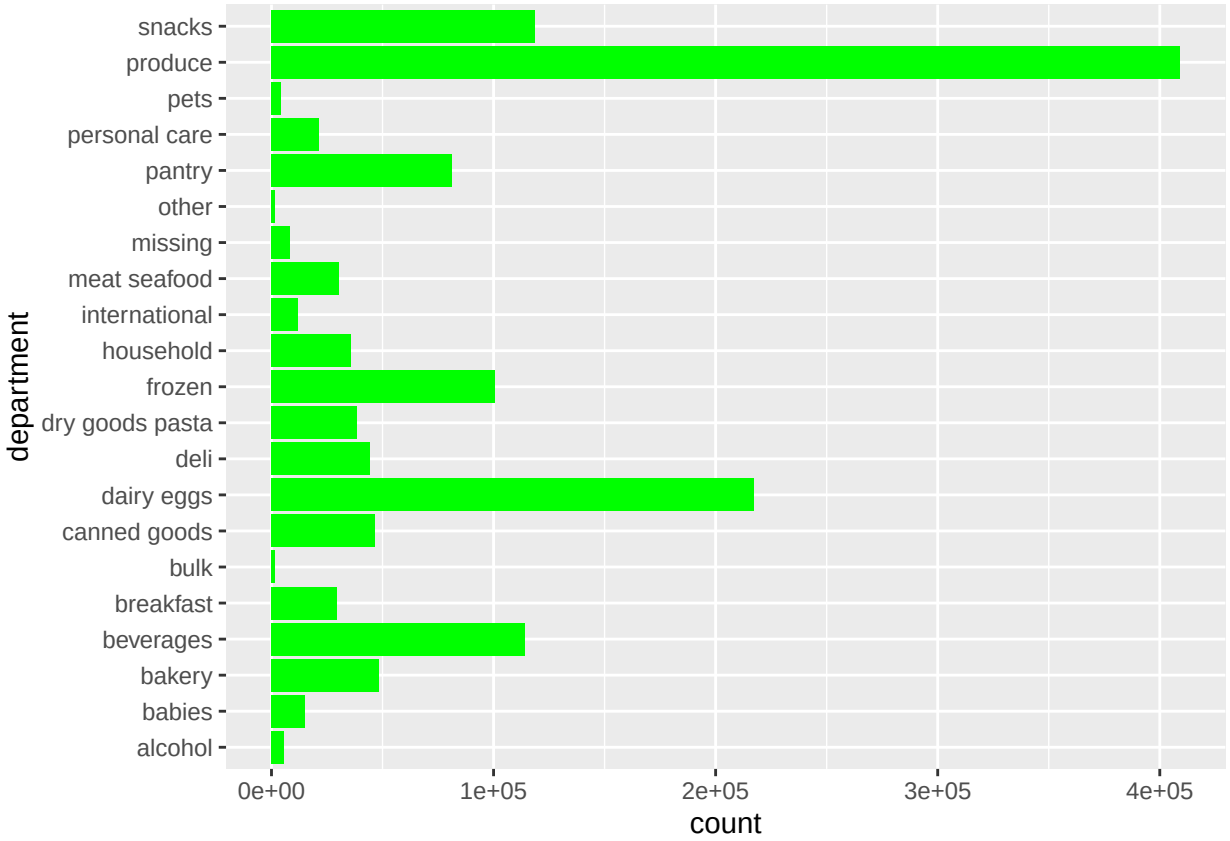



People mostly order from 8:00 - 17:00 (8AM - 5PM).

Most frequently bought products

```
X %>% ggplot(aes(x= department)) +
  geom_histogram(stat="count", fill="green")+
  coord_flip()
```

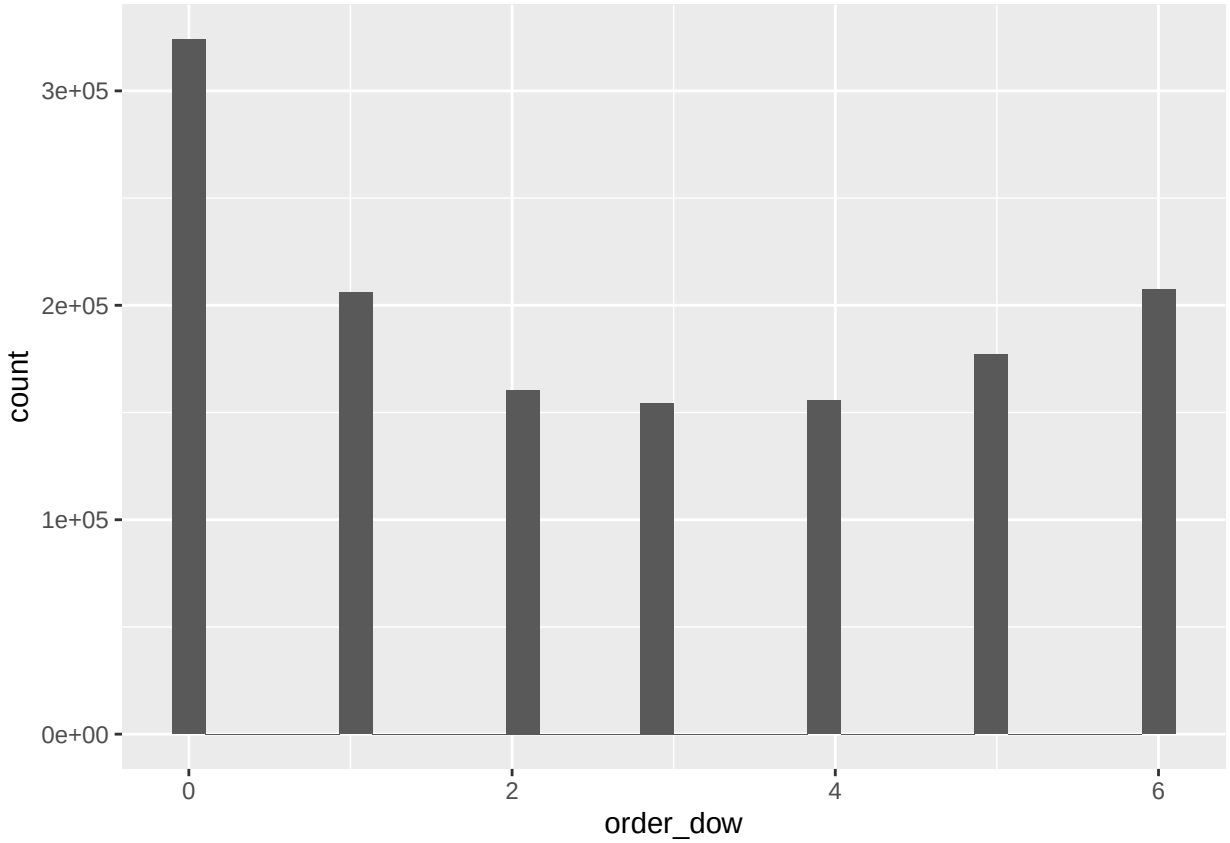
```
## Warning: Ignoring unknown parameters: binwidth, bins, pad
```




Most orders come from the produce aisle, with snacks and dairy, eggs among the top 3 department aisles. 'order_dow' is the day of week. Which days are orders more commonly placed on?

```
X %>% ggplot(aes(x=order_dow))+
      geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

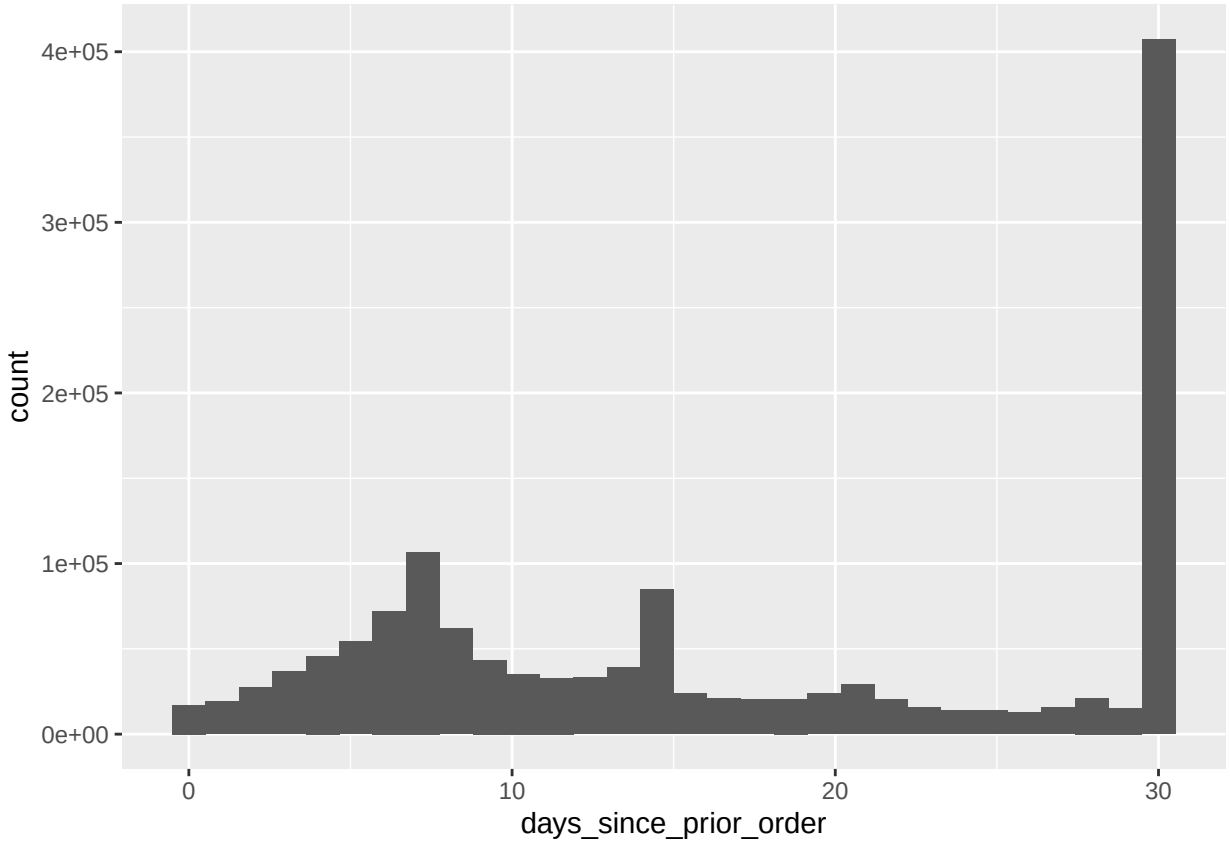



```
#Sunday, Monday and Saturday appear to be the most common days where people place their orders.
```

How many days pass between an order and the next order?

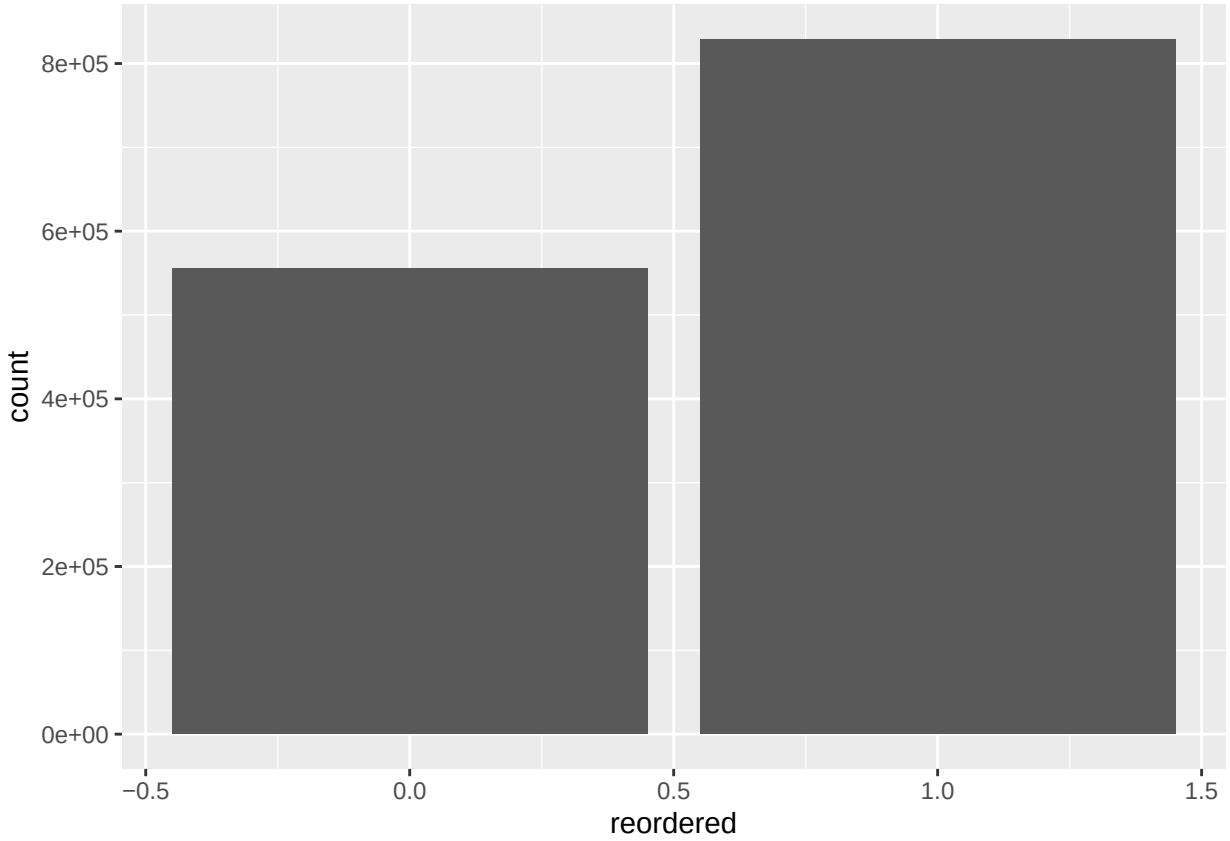
```
X %>% ggplot(aes(x=days_since_prior_order))+
      geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




People most commonly order again after 30 days (1 month), or 7 days (1 week).

```
  ggplot(X) +
geom_bar(mapping= aes(x=reordered))
```




X_merge column is not needed for association rule mining, so can set to NULL:

```
X$X_merge <- NULL
```

Need to convert dataframe to transaction data so that all items bought together in one order is in one row. Currently different products from the same order are in their own rows (singles format).

```
library(plyr)
```

```
## ------------------------------------------------------------------------------

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

## ------------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following object is masked from 'package:purrr':
##
##     compact
```

```
## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```
#ddply(dataframe, variables_to_be_used_to_split_data_frame, function_to_be_applied)

transactionData <- ddply(X, c("order_id","user_id"),
                         function(df1)paste(df1$product_name,     #paste is used to concatenate vectors t
                         collapse = ","))     #collapse is used to separate the concatenated product name
```

Look at the transaction data. This is currently in the form of a basket format:

#set order id and user id to NULL in the transaction dataset since it will not be needed for item association

```
transactionData$order_id <- NULL
transactionData$user_id <- NULL
```

rename column to items

```
colnames(transactionData) <- c("items")
```

write the transaction data csv into a csv file:

```
#write.csv(transactionData,"C:/Users/qt09n/Desktop/Project/market_basket_transactions.csv", quote = FAL
```

take the transaction data file which is in basket format and convert it to an object of the transaction class

```
tr
```

```
## transactions in sparse format with
##  131210 transactions (rows) and
##  50153 items (columns)
```

```
summary(tr)
```

```
## transactions as itemMatrix in sparse format with
##  131210 rows (elements/itemsets/transactions) and
##  50153 columns (items) and a density of 0.00020449
##
## most frequent items:
##                 Banana Bag of Organic Bananas   Organic Strawberries
##                  17724                 14597                  10260
##   Organic Baby Spinach            Large Lemon                (Other)
##                   9318                  7740                1286023
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 7750 8047 8474 8470 8887 8684 8471 7856 7104 6447 5943 5356 4770 4219 3645 3364
##   17   18   19   20   21   22   23   24   25   26   27   28   29   30   31   32
```

```
## 3073 2617 2390 2020 1771 1560 1408 1245 1085  932  812  637  557  553  434  387
##   33   34   35   36   37   38   39   40   41   42   43   44   45   46   47   48
##  299  289  246  190  178  151  126  116   84   82   71   63   49   43   35   28
##   49   50   51   52   53   54   55   56   57   58   59   60   61   62   63   65
##   21   22   20   23   17   13    8   11    5    5    5    8    5    3    3    1
##   66   67   68   69   72   75   76   78   80   82   84
##    4    3    2    5    1    1    1    2    1    1    1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    5.00    8.00   10.26   14.00   84.00
##
## includes extended item information - examples:
##                          labels
## 1                            #2
## 2            #2 Coffee Filters
## 3 #2 Cone White Coffee Filters
```

131210 transactions (rows) and 50153 items (columns). 50153 is the product names. Density is the percentage of non-zero cells in a sparse matrix, which is the total number of items purchased divided by a possible number of items in that matrix.

To calculate how many items were purchased: 131210 x 50153 x 0.00020449 = 1345662

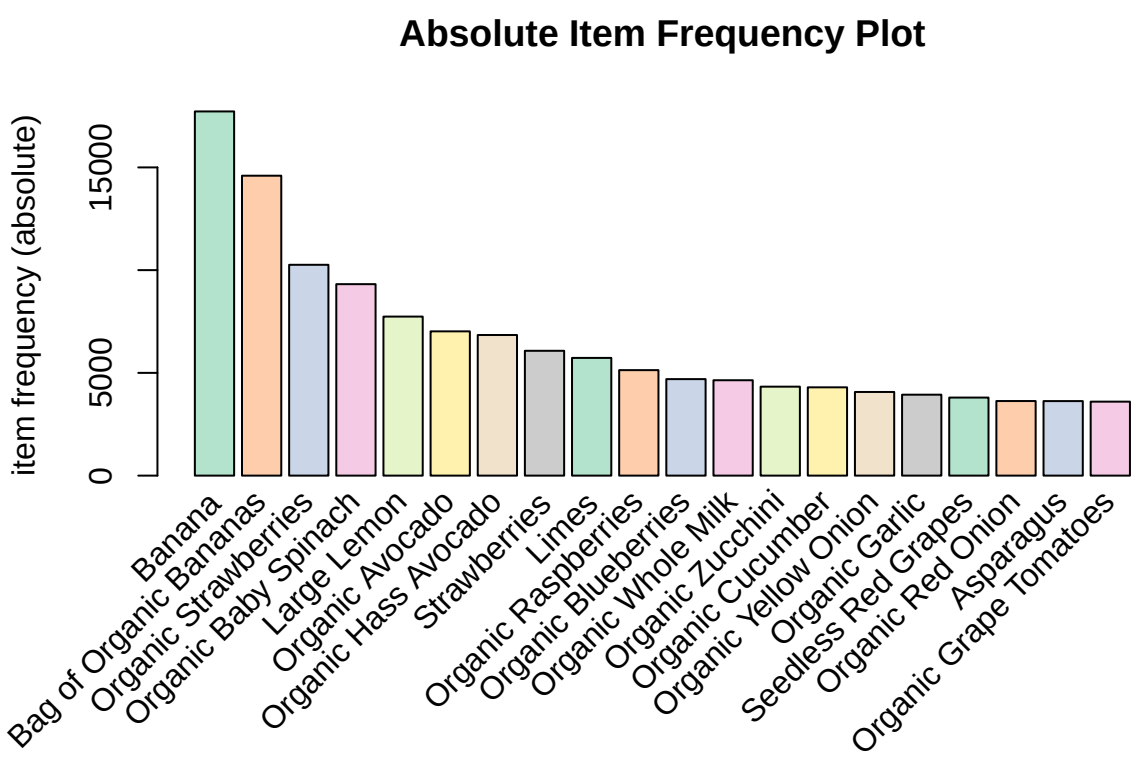
A sparse matrix is a matrix in which most elements are zero.

Element (itemset/transaction) length distribution. This section is about how many transactions containing a certain number of items. The first row is the number of items in a transaction, and the second row is the number of transactions with that number of items. ie. There are 1877502617 transactions with only 1 item. There are 1980472390 transactions with 2 items.

To generate an item Frequency Plot to view the distribution of objects basedon itemMatrix.

Create an item frequency plot for the top 50 items.

```
itemFrequencyPlot(tr, topN=20, type="absolute", col=brewer.pal(8, 'Pastel2'), main="Absolute Item Frequ
```

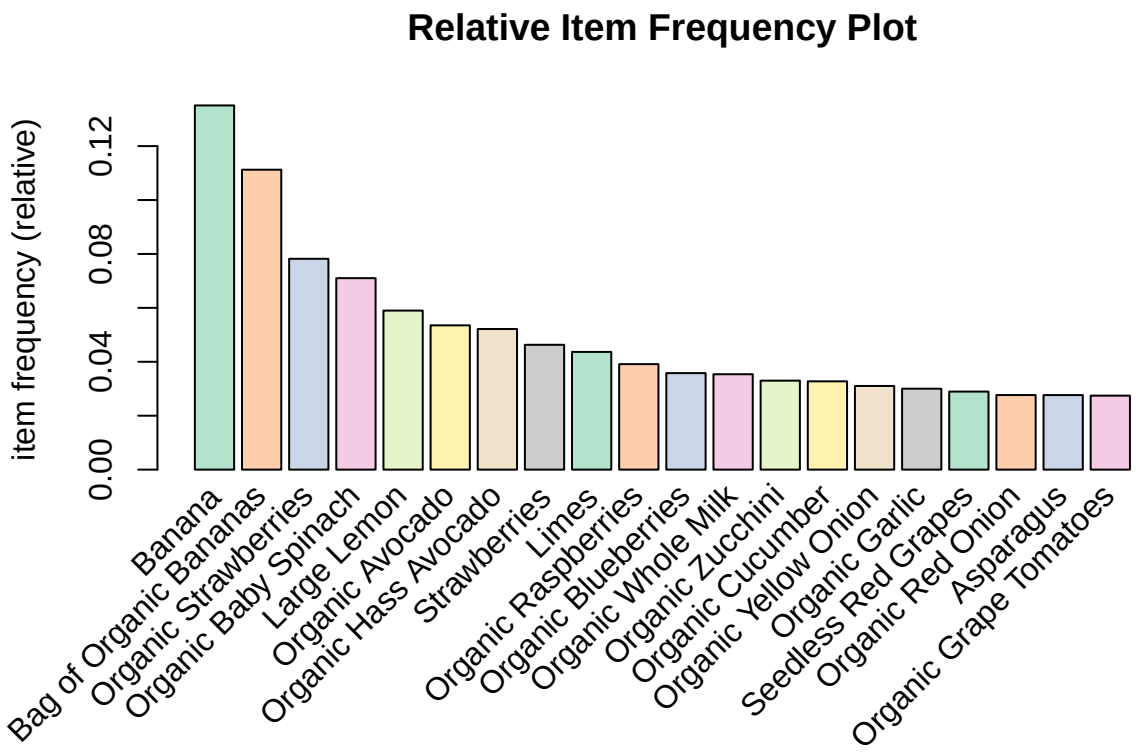



According to the frequency plot, the top 20 products bought in Instacart are banana, bag of organic bananas, organic strawberries, organic baby spinach, large lemon, organic avocado, organic hass avocado, strawberries, limes, organic raspberries, organic blueberries, organic whole milk, organic zucchini, organic cucumber, organic yellow onion, organic garlic, seedless red grapes, organic red onion, asparagus and organic grape tomatoes.

This plot shows absolute frequency which are independent numeric frequencies for each item.

To look at relative frequencies (how many times an item appears in comparison to others):

```
itemFrequencyPlot(tr, topN=20, type="relative", col=brewer.pal(8, 'Pastel2'), main="Relative Item Frequ
```




### Generating Rules

Mine the rules using APRIORI algorithm.

```
association.rules <- apriori(tr, parameter= list(supp=0.001, conf=0.8, maxlen=10))
```

```
## 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
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 131
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[50153 item(s), 131210 transaction(s)] done [0.63s].
## sorting and recoding items ... [1812 item(s)] done [0.01s].
## creating transaction tree ... done [0.06s].
## checking subsets of size 1 2 3 4 done [0.06s].
## writing ... [255 rule(s)] done [0.00s].
## creating S4 object  ... done [0.01s].
```

The apriori will take tr as the transaction object to apply the rule mining. Parameters allow you to set min_sup and min_confidence and min confidence of 0.8, maximum of 10 items(maxlen).

```
summary(association.rules)
```

```
## set of 255 rules
##
## rule length distribution (lhs + rhs):sizes
##   2   3   4
## 132 111  12
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   2.000   2.000   2.529   3.000   4.000
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001021   Min.   :0.8017   Min.   :0.001021   Min.   : 39.52
##  1st Qu.:0.001143   1st Qu.:0.9917   1st Qu.:0.001174   1st Qu.:185.06
##  Median :0.001296   Median :1.0000   Median :0.001364   Median :394.02
##  Mean   :0.001892   Mean   :0.9800   Mean   :0.001940   Mean   :438.96
##  3rd Qu.:0.002043   3rd Qu.:1.0000   3rd Qu.:0.002058   3rd Qu.:701.98
##  Max.   :0.007522   Max.   :1.0000   Max.   :0.007522   Max.   :979.18
##      count
##  Min.   :134.0
##  1st Qu.:150.0
##  Median :170.0
##  Mean   :248.3
##  3rd Qu.:268.0
##  Max.   :987.0
##
## mining info:
##  data ntransactions support confidence
##    tr        131210   0.001        0.8
```

set of 255 rules were generated from the apriori algorithm.

to look at just the top 10 rules:

```
inspect(association.rules[1:10])
```

```
##      lhs                    rhs                        support     confidence
## [1]  {Mini & Mobile}     => {Natural Artesian Water} 0.001036506 1
## [2]  {Americano}         => {Prosciutto}             0.001021264 1
## [3]  {1000 Sheet Rolls} => {1â??Ply}                 0.001036506 1
## [4]  {1â??Ply}           => {1000 Sheet Rolls}       0.001036506 1
## [5]  {1000 Sheet Rolls} => {Bathroom Tissue}        0.001036506 1
## [6]  {1â??Ply}           => {Bathroom Tissue}        0.001036506 1
## [7]  {Twin Pack}         => {French Baguettes}       0.001021264 1
## [8]  {French Baguettes} => {Twin Pack}              0.001021264 1
## [9]  {Twin Pack}         => {Take & Bake}            0.001021264 1
## [10] {Take & Bake}       => {Twin Pack}              0.001021264 1
##      coverage    lift     count
## [1]  0.001036506 198.8030 136
```

```
## [2]  0.001021264 372.7557 134
## [3]  0.001036506 964.7794 136
## [4]  0.001036506 964.7794 136
## [5]  0.001036506 493.2707 136
## [6]  0.001036506 493.2707 136
## [7]  0.001021264 979.1791 134
## [8]  0.001021264 979.1791 134
## [9]  0.001021264 979.1791 134
## [10] 0.001021264 979.1791 134
```

136 transactions where customers who bought Mini and Mobile also bough Natural Artesian Water. 136 transactions where people who bought 1000 sheet Rolls also bought 1a Ply, and 136 transactions where people who bought 1000 Sheet Rolls also bought Bathroom tissue.

### Limiting the number and size of rules

Setting the the conf value and maxlen parameter to higher values will give stronger rules.

```
shorter_association_rules <- apriori(tr, parameter = list(supp=0.001, conf=0.9, maxlen=5))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.9    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##       5  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 131
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[50153 item(s), 131210 transaction(s)] done [0.63s].
## sorting and recoding items ... [1812 item(s)] done [0.01s].
## creating transaction tree ... done [0.06s].
## checking subsets of size 1 2 3 4 done [0.06s].
## writing ... [231 rule(s)] done [0.00s].
## creating S4 object  ... done [0.02s].
```

```
summary(shorter_association_rules)
```

```
## set of 231 rules
##
## rule length distribution (lhs + rhs):sizes
##   2   3   4
## 121  98  12
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   2.000   2.000   2.528   3.000   4.000
```

```
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001021   Min.   :0.9066   Min.   :0.001021   Min.   : 55.65
##  1st Qu.:0.001143   1st Qu.:1.0000   1st Qu.:0.001158   1st Qu.:202.80
##  Median :0.001296   Median :1.0000   Median :0.001303   Median :435.52
##  Mean   :0.001871   Mean   :0.9932   Mean   :0.001885   Mean   :452.06
##  3rd Qu.:0.002043   3rd Qu.:1.0000   3rd Qu.:0.002050   3rd Qu.:720.96
##  Max.   :0.007522   Max.   :1.0000   Max.   :0.007522   Max.   :979.18
##      count
##  Min.   :134.0
##  1st Qu.:150.0
##  Median :170.0
##  Mean   :245.5
##  3rd Qu.:268.0
##  Max.   :987.0
##
## mining info:
##  data ntransactions support confidence
##    tr        131210   0.001        0.9
```

```
inspect(shorter_association_rules[1:10])
```

```
##      lhs                    rhs                        support     confidence
## [1]  {Mini & Mobile}     => {Natural Artesian Water} 0.001036506 1
## [2]  {Americano}         => {Prosciutto}             0.001021264 1
## [3]  {1000 Sheet Rolls} => {1â??Ply}                0.001036506 1
## [4]  {1â??Ply}           => {1000 Sheet Rolls}       0.001036506 1
## [5]  {1000 Sheet Rolls} => {Bathroom Tissue}        0.001036506 1
## [6]  {1â??Ply}           => {Bathroom Tissue}        0.001036506 1
## [7]  {Twin Pack}         => {French Baguettes}       0.001021264 1
## [8]  {French Baguettes} => {Twin Pack}              0.001021264 1
## [9]  {Twin Pack}         => {Take & Bake}            0.001021264 1
## [10] {Take & Bake}       => {Twin Pack}              0.001021264 1
##      coverage    lift     count
## [1]  0.001036506 198.8030 136
## [2]  0.001021264 372.7557 134
## [3]  0.001036506 964.7794 136
## [4]  0.001036506 964.7794 136
## [5]  0.001036506 493.2707 136
## [6]  0.001036506 493.2707 136
## [7]  0.001021264 979.1791 134
## [8]  0.001021264 979.1791 134
## [9]  0.001021264 979.1791 134
## [10] 0.001021264 979.1791 134
```

To remove redundant rules

```
subset.rules <- which(colSums(is.subset(association.rules, association.rules))>1)  #get subset rules in
length(subset.rules)
```

```
## [1] 200
```

```
#which() - gives you the position of elements in the vector where value = TRUE
#colSums() - row and column sums for dataframes and numeric arrays
#is.subset() - find out if elements of one vector contain all elements of other vector
```

To remove the subset rules:

```
subset.association.rules <- association.rules[-subset.rules] #remove subset rules
```

To find out what customers buy before buying a certain product, use the appearance option in the apriori command. ie. to find out what people buy before buying French baguettes:

```
baguette.association.rules <- apriori(tr, parameter = list(supp=0.001, conf=0.8), appearance = list(defa
```

```
## 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
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 131
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[50153 item(s), 131210 transaction(s)] done [0.62s].
## sorting and recoding items ... [1812 item(s)] done [0.02s].
## creating transaction tree ... done [0.05s].
## checking subsets of size 1 2 3 4 done [0.06s].
## writing ... [3 rule(s)] done [0.01s].
## creating S4 object  ... done [0.01s].
```

To find out how many customers buy French baguettes along with other items:

```
inspect(head(baguette.association.rules))
```

```
##     lhs                          rhs                 support     confidence
## [1] {Take & Bake}             => {French Baguettes} 0.001021264 1
## [2] {Twin Pack}               => {French Baguettes} 0.001021264 1
## [3] {Take & Bake,Twin Pack} => {French Baguettes} 0.001021264 1
##     coverage    lift     count
## [1] 0.001021264 979.1791 134
## [2] 0.001021264 979.1791 134
## [3] 0.001021264 979.1791 134
```

To find out answer to "What other items did customers who bought X item also buy?" ...ie. for French baguettes again:

```
baguette.association.rules <- apriori(tr, parameter = list(supp=0.001, conf=0.8), appearance = list(lhs=
```

```
## 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
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 131
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[50153 item(s), 131210 transaction(s)] done [0.60s].
## sorting and recoding items ... [1812 item(s)] done [0.02s].
## creating transaction tree ... done [0.05s].
## checking subsets of size 1 2 done [0.01s].
## writing ... [2 rule(s)] done [0.00s].
## creating S4 object  ... done [0.01s].
```

Keep lhs as French Baguettes because you want to find out the probability of how many customers buy French baguettes with other items:

```
inspect(head(baguette.association.rules))
```

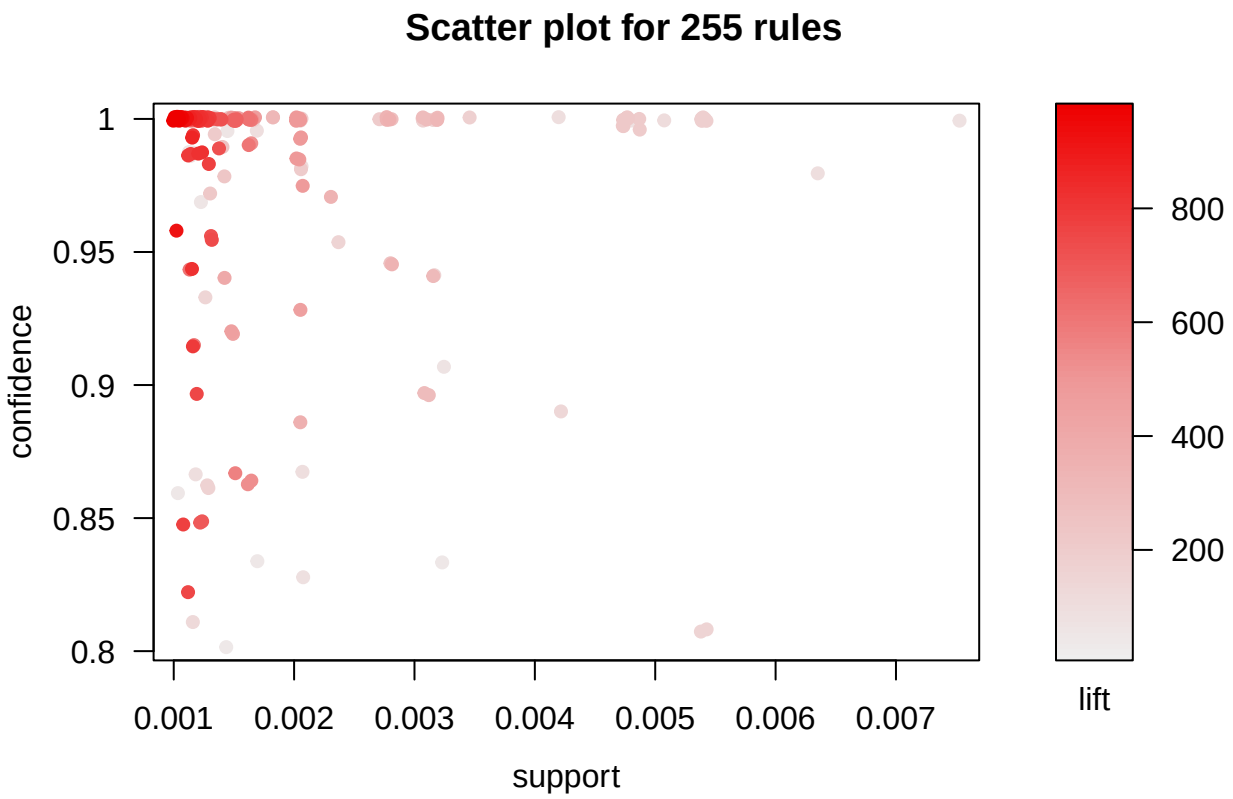
```
##     lhs                   rhs           support     confidence coverage
## [1] {French Baguettes} => {Take & Bake} 0.001021264 1          0.001021264
## [2] {French Baguettes} => {Twin Pack}   0.001021264 1          0.001021264
##     lift     count
## [1] 979.1791 134
## [2] 979.1791 134
```

Scatterplot

```
#filter rules with confidence greater than 0.6 or 60%
subRules <- association.rules[quality(association.rules)$confidence>0.6]

#plot subrules
plot(subRules)
```

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

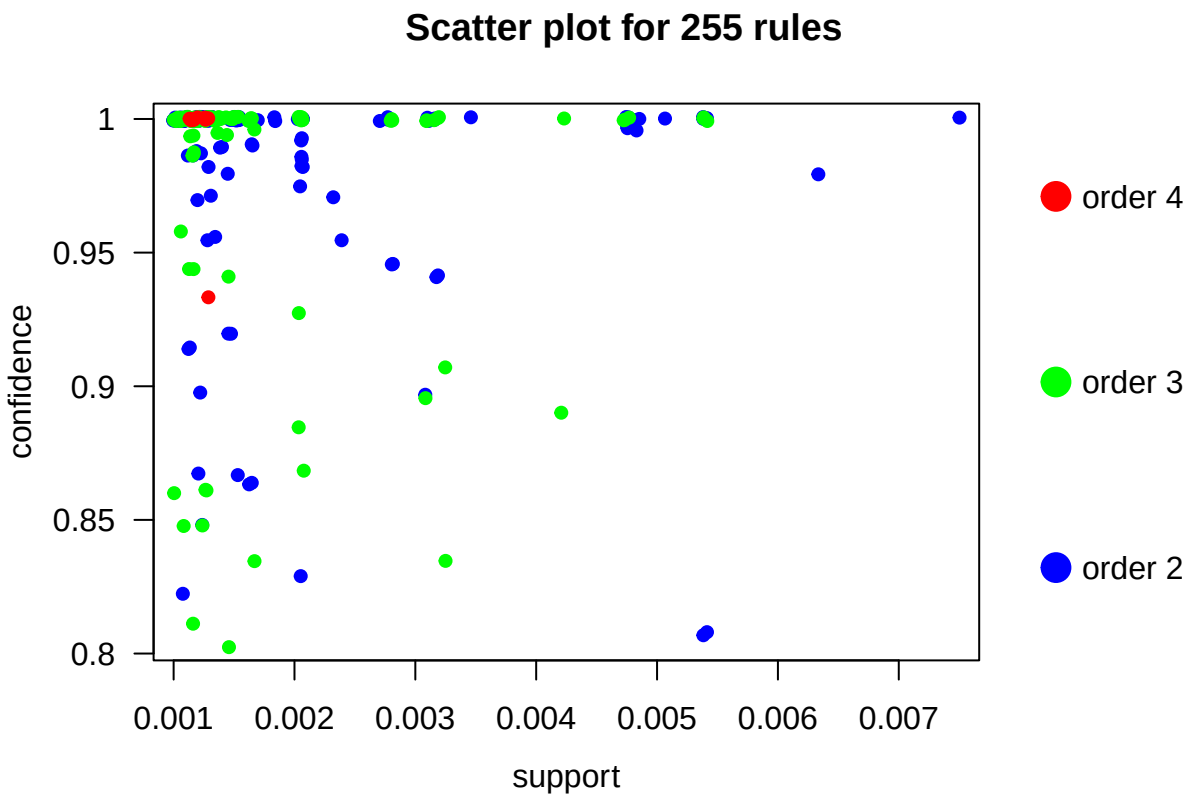



Rules with high lift have low support

Plot options: rulesObject = rules object to be plotted measure= measures for rule interestingness ie. support, confidence, lift or combination of these depending on method value shading = measure used to color points( support, confidence, lift); default=lift metho=visualization method to be used(scatterplot, 2 key plot, matrix3D)

```
plot(subRules, method="two-key plot")
```

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



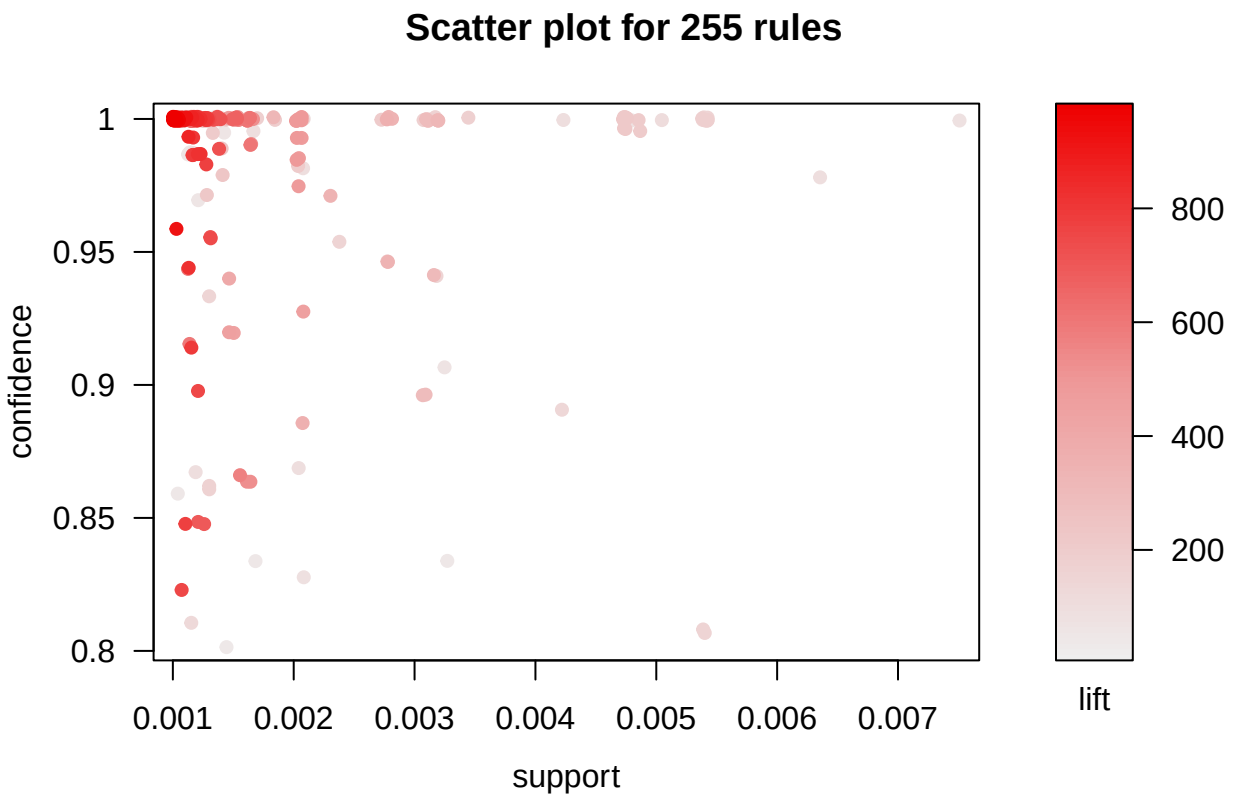

Two key plot has support on x axis and confidence on y-axis. It uses order for coloring. Order is the number of items in the rule.

**Interactive Scatterplot**

Users can hover over rules and see the quality measures(support, confidence and lift).

```
plot(subRules)
```

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



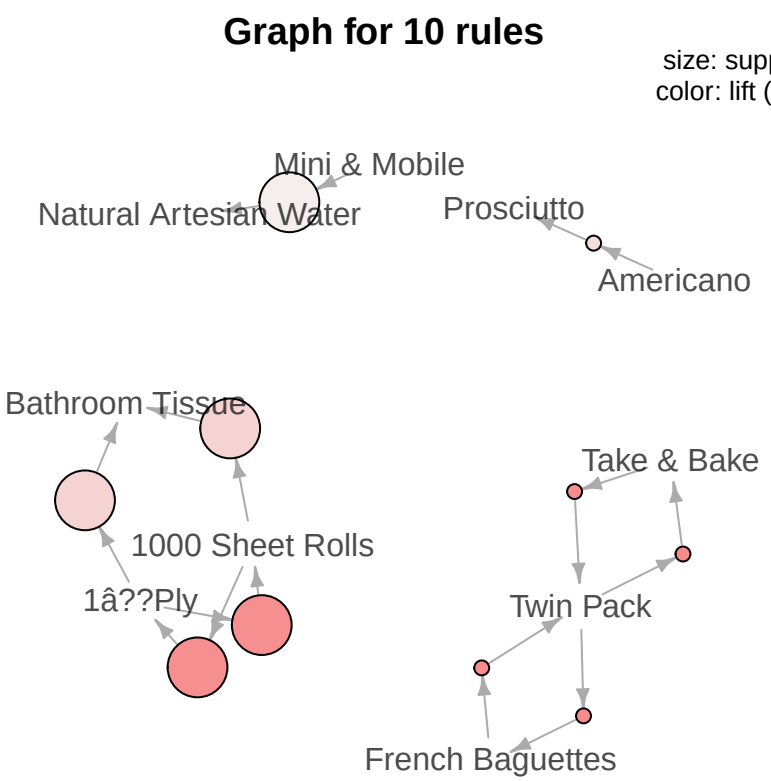

Graph based methods: vertices are labeled with item names; item sets or rules are indicated with a second set of vertices: arrows point from items to rule vertices = LHS; arrow from rule to an item = RHS. Size & color = interest measure.

To get the top 10 rules with highest confidence:

```
top10subRules <- head(subRules, n= 10, by="confidence")
```

Make interactive plot with engine=htmlwidget parameter in plot

```
# plot(top10subRules, method="graph", engine="htmlwidget")   #html widget can not be shown in pdf
plot(top10subRules, method="graph")
```



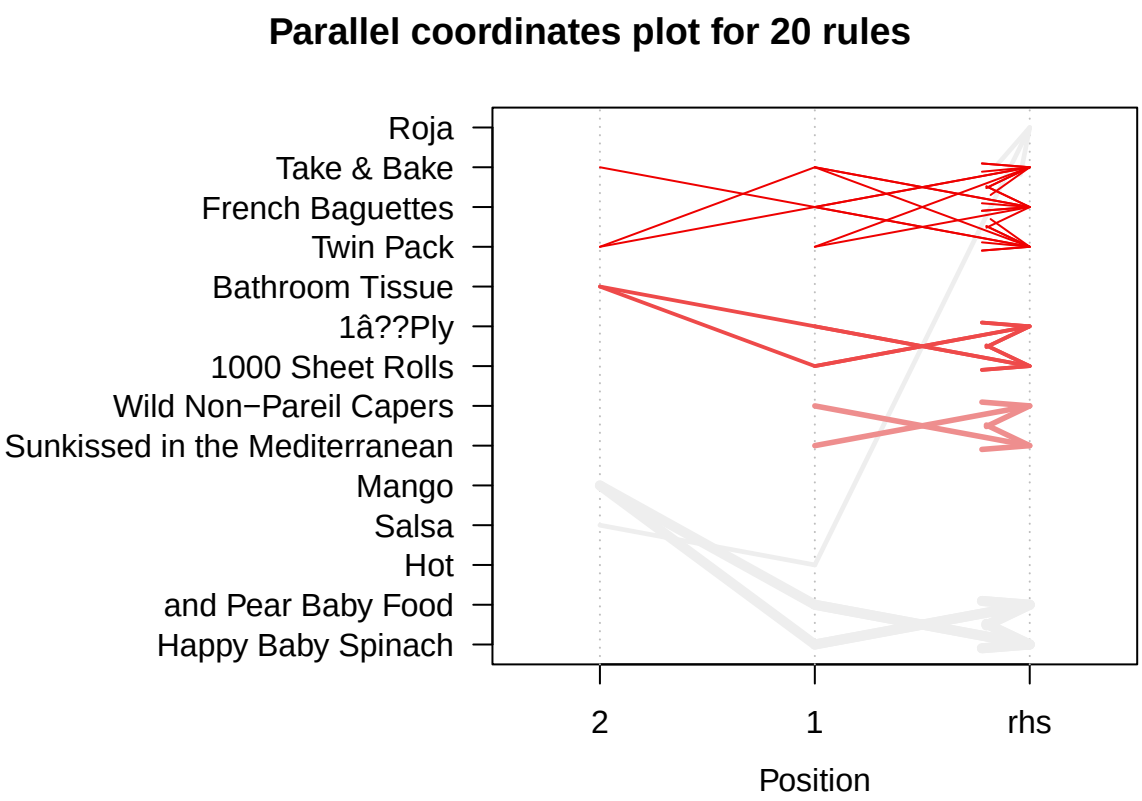

To export graphs for sets of association rules in GraphML format (which you can open with Gephi tool):

```
saveAsGraph(head(subRules, n=1000, by="lift"), file="rules.graphml")
```

### Individual Rule Representation

This is Parallel Coordinates Plot, used to visualize products with items and types of sales: RHS = consequent, which is item that is suggested for customers to buy: positions are LHS, where 2 = most recent item; and 1=item previously bought

```
#filter top 20 rules with highest lift:
subRules2 <-head(subRules, n=20, by="lift")
plot(subRules2, method="paracoord")
```




According to this plot, if when someone buys salsa, and "hot".., they are likely to buy Roja.

If someone has mango, and pear baby food in their cart, they are likely to buy Happy Baby Spinach as well.

## References

https://www.datacamp.com/community/tutorials/market-basket-analysis-r#code

https://datascienceplus.com/a-gentle-introduction-on-market-basket-analysis%E2%80%8A-%E2%80%8Aassociation-rules/

https://en.wikipedia.org/wiki/Sparse_matrix

https://cran.r-project.org/web/packages/arulesViz/vignettes/arulesViz.pdf