ML1000 Assignment 3

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Abstract

The main goal of recommender systems is to provide suggestions to online users to make better decisions from many alternatives available over the Web. A better recommender system is directed more towards personalized recommendations by taking into consideration information about a product, such as specifications, users' purchase history, comparison with other products, and so on, before making recommendations.

Business Case

Data Understanding

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)

How do we merge the data files?

There are six data files, excluding the sample_submission.csv file, from the Instacart Market Basket Analysis data - aisles.csv, departments.csv, order_products___train.csv, order_products___prior.csv, orders.csv and products.csv.

Data file descriptions

aisles.csv - contains aisle id and aisle description columns

departments.csv - contains department id and department description columns

order_products___*.csv - These files specify which products were purchased in each order. order_products___prior.csv contains previous order contents for all customers. 'reordered' indicates that the customer has a previous order that contains the product. order_products_train.csv contains order information for transactions which will be used for training the model.

orders.csv - This file tells to which set (prior, train, test) an order belongs. You are predicting reordered items only for the test set orders. 'order_dow' is the day of week.

products.csv - contains product_id, product_name, aisle_id, department_id

Steps to merge the data files:

1. Merged the aisles data with the products data to obtain Merged dataset 1, so that we know which aisle each product belongs to.

2. Combined the Merged dataset 1 with the department data to obtain Merged dataset 2, so we know which aisle and department each product is from.

3. Add Merged dataset 2, which contains product full information, to order_products___train and order_products___prior files, respectively, to obtain Merged dataset 3 (Train) and Merged dataset 4 (Prior), so that we know the product information (e.g. product names, aisles and departments they belong to) of the products in the training and prior orders.

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 f
##  $ 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 ...
```

```
dim(X)
```

```
## [1] 1384617      16
```

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),]
```

```
sum(is.na(X))
```

```
## [1] 0
```

No missing values in dataset.

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
```

```r
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
```

Check total users:

```r
user_count <- unique(X$user_id)
length(user_count)
```

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

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

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

```r
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
```

```r
#134 aisles
```

```r
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
```

```r
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"
```

```r
#21 departments
```

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

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

```r
#39123 products
```

Total products from product id column:

```r
product_count <- unique(X$product_id)
length(product_count)
```

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

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

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

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

How many unique orders are in the training dataset?

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

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

How many users are in the training dataset?

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

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

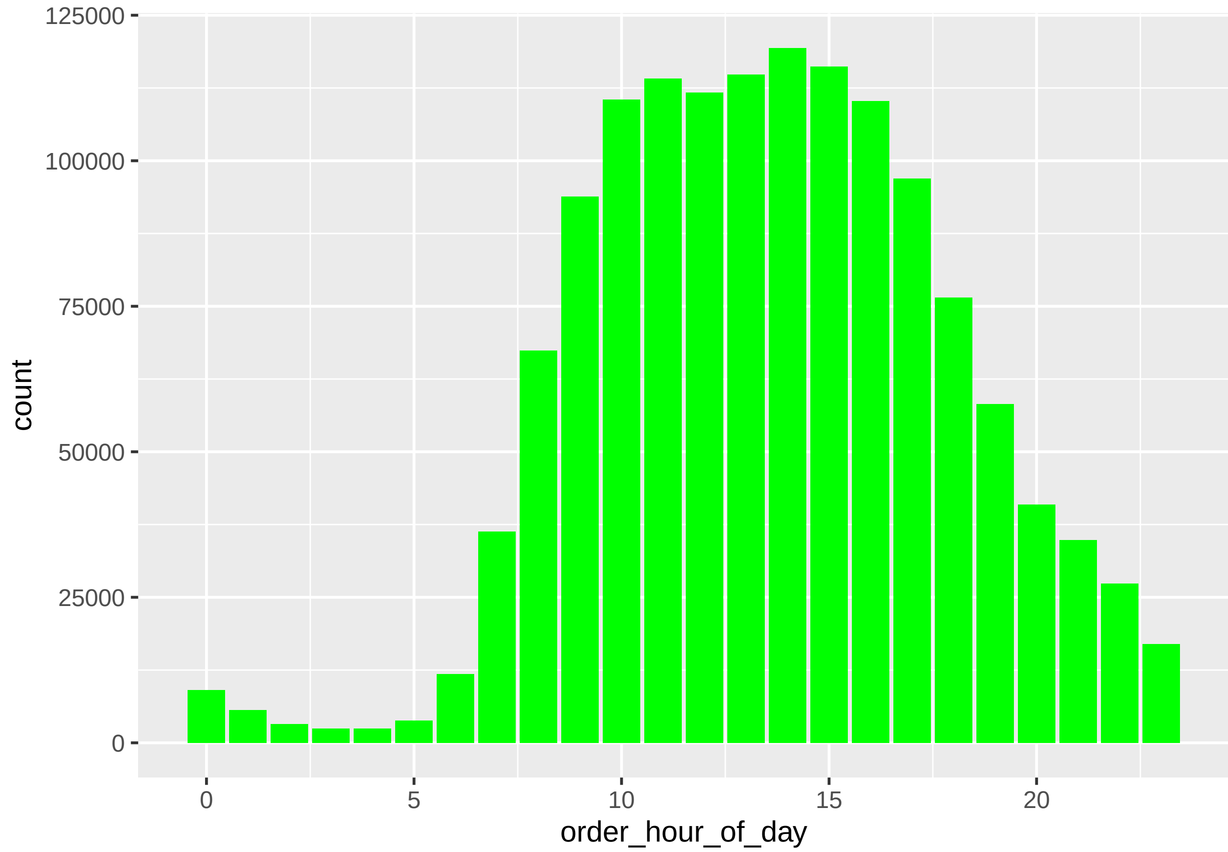
So it looks like the number of users are the same as the number of orders…

Recode order_hour_of_day to numeric:

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

Look at when people order:

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

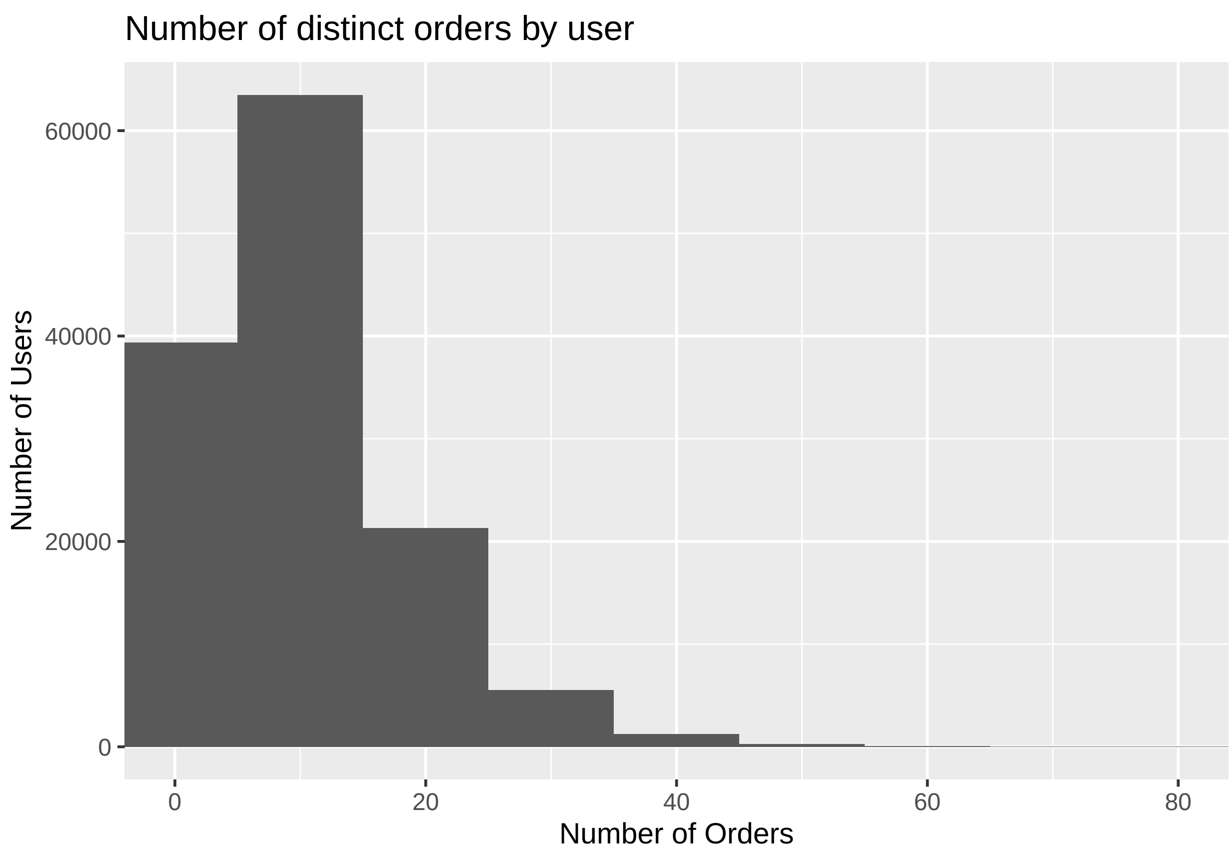


People mostly order from 8:00 - 17:00 (8AM - 5PM).

Number of distinct orders by user:

```r
p1<-X %>%
  group_by(user_id) %>%
  dplyr::summarise(count_order=n()) %>%
  ungroup()

ggplot(p1, aes(count_order)) + geom_histogram(binwidth = 10)+labs(title="Number of distinct orders by us
        x ="Number of Orders", y = "Number of Users")+coord_cartesian(xlim = c(0, 80))
```

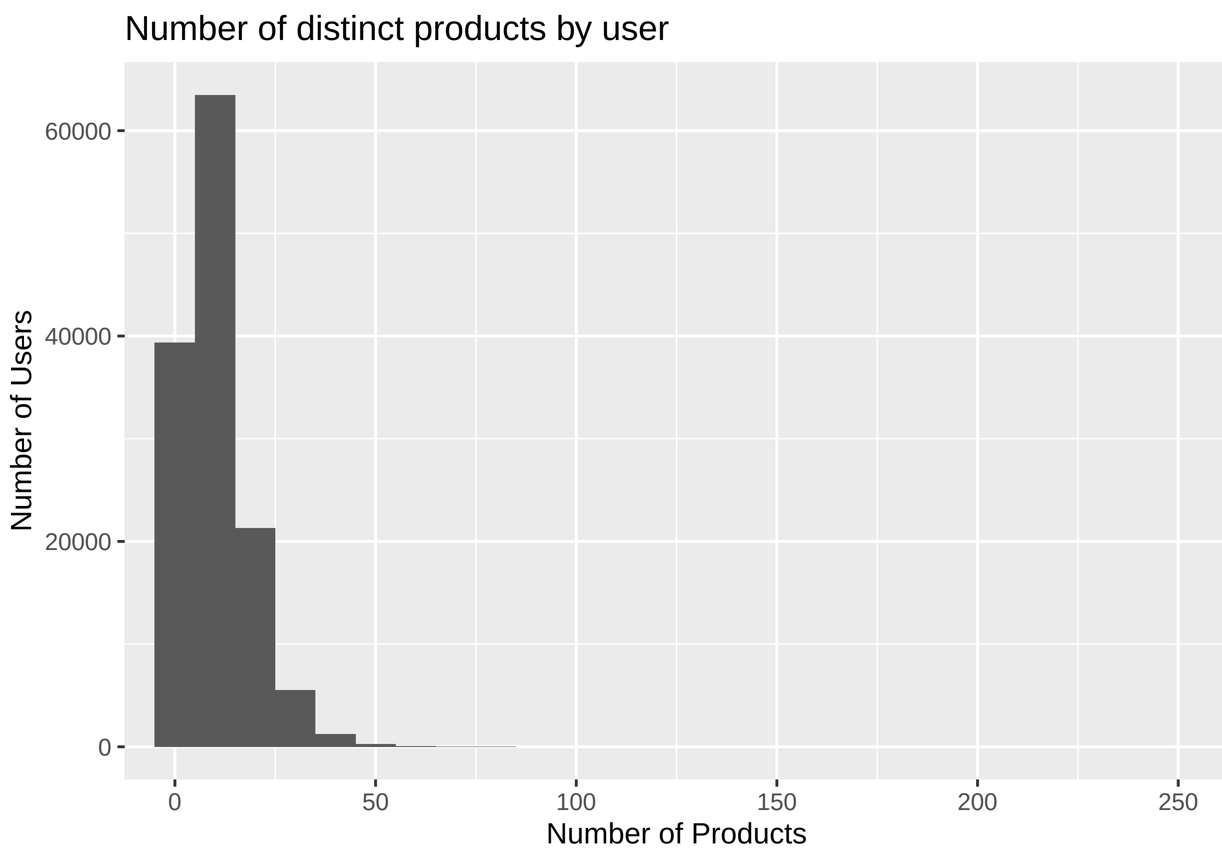


Number of distinct products per user:

```
p2 <- X %>%
  group_by(user_id, product_id) %>%
  dplyr::summarise(count3=n()) %>%
  select(user_id, product_id, count3) %>%
  ungroup() %>%
  group_by(user_id) %>%
  dplyr::summarise(count_product=n()) %>%
  ungroup()
```

```
## `summarise()` has grouped output by 'user_id'. You can override using the `.groups` argument.
```

```
ggplot(p2, aes(count_product)) + geom_histogram(binwidth = 10)+labs(title="Number of distinct products 
        x ="Number of Products", y = "Number of Users")+coord_cartesian(xlim = c(0, 250))
```

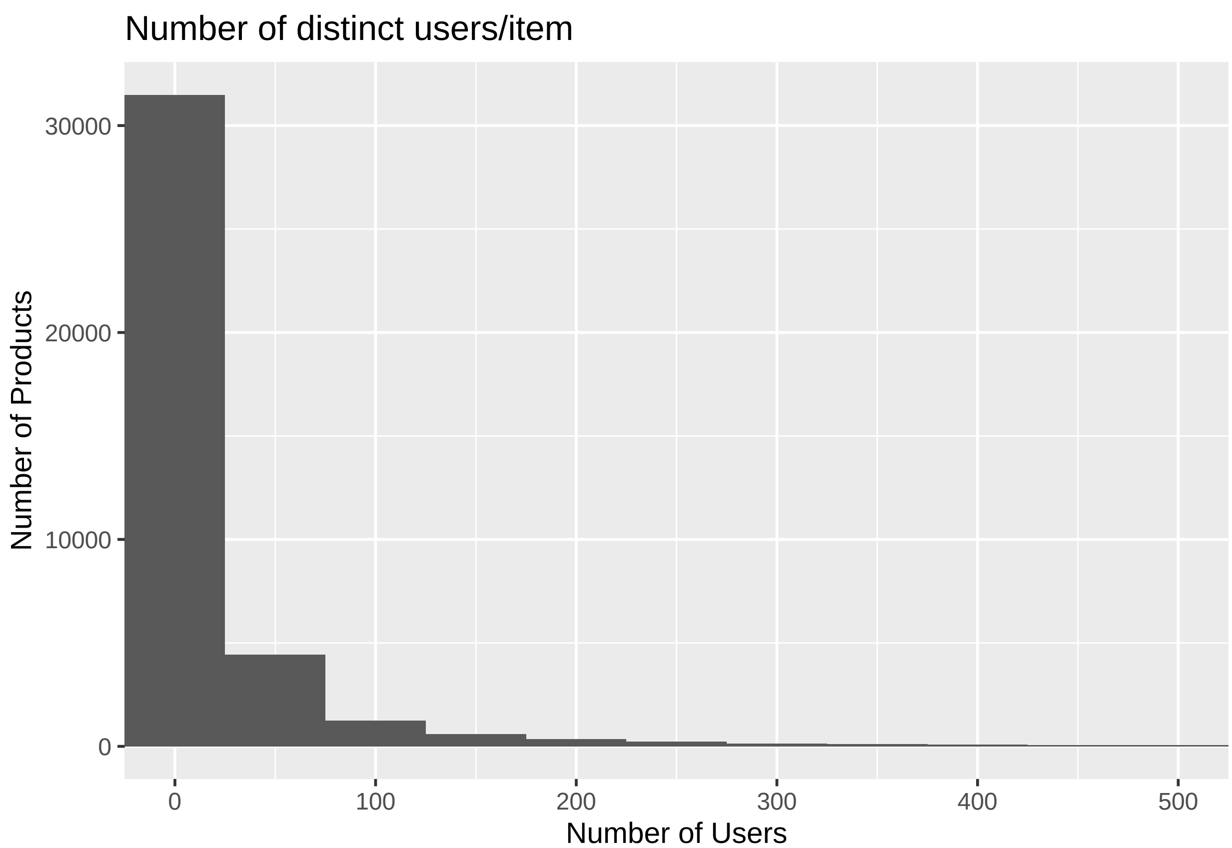


Number of distinct users/item

```
p3 <- X %>%
  group_by(product_id,user_id) %>%
  dplyr::summarise(count4=n()) %>%
  select(user_id,product_id,count4) %>%
  ungroup() %>%
  group_by(product_id) %>%
  dplyr::summarise(count_user=n()) %>%
  ungroup()
```

```
## `summarise()` has grouped output by 'product_id'. You can override using the `.groups` argument.
```

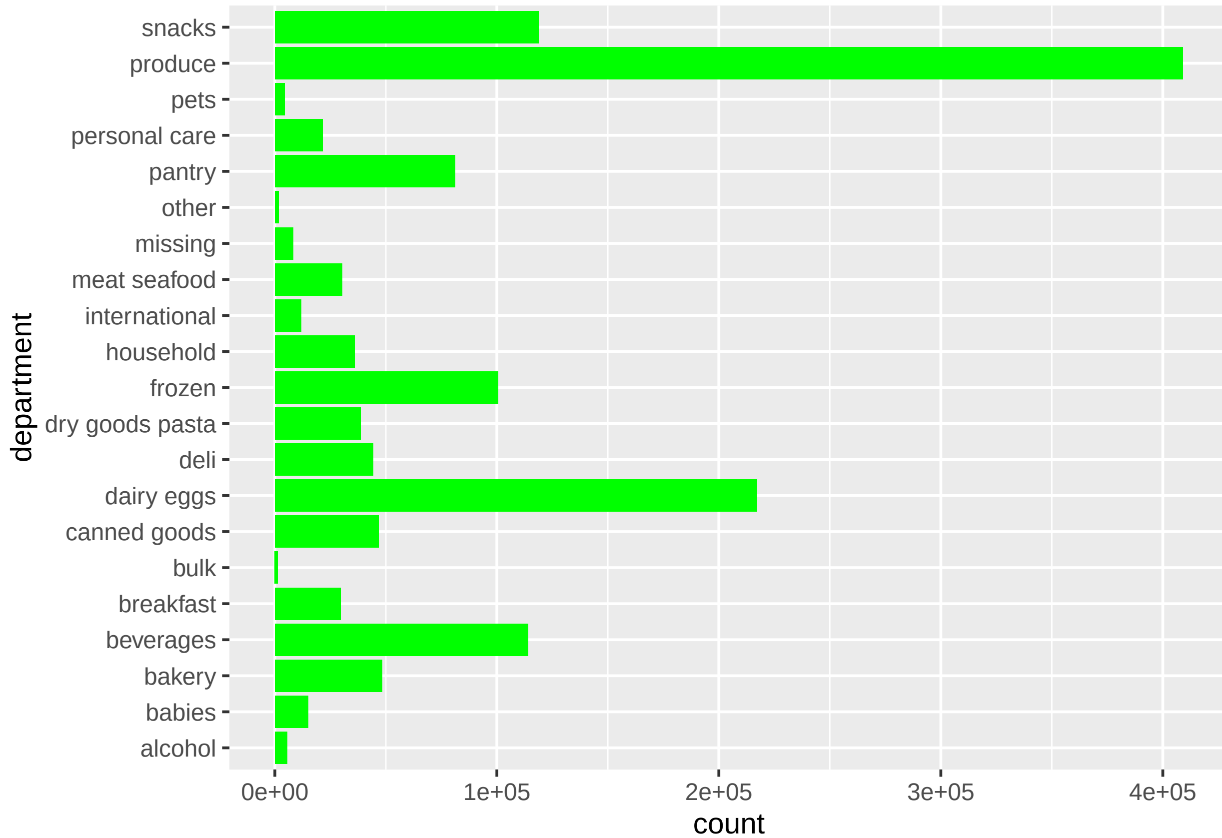
```
ggplot(p3, aes(count_user)) + geom_histogram(binwidth = 50)+labs(title="Number of distinct users/item",
        x ="Number of Users", y = "Number of Products")+coord_cartesian(xlim = c(0, 500))
```



Most frequently bought products

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

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

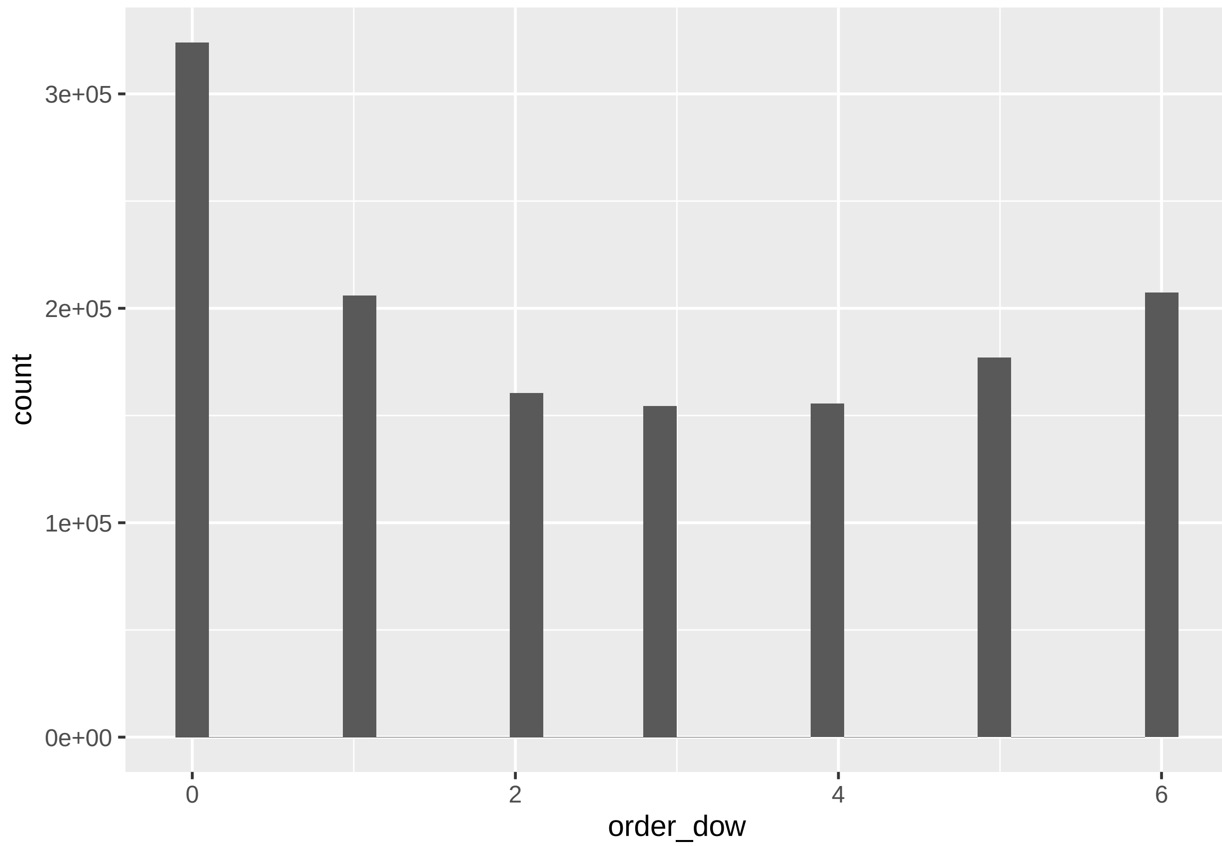


Most orders come from the produce aisle, with snacks and dairy, eggs among the top 3 department aisles.

'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`.
```

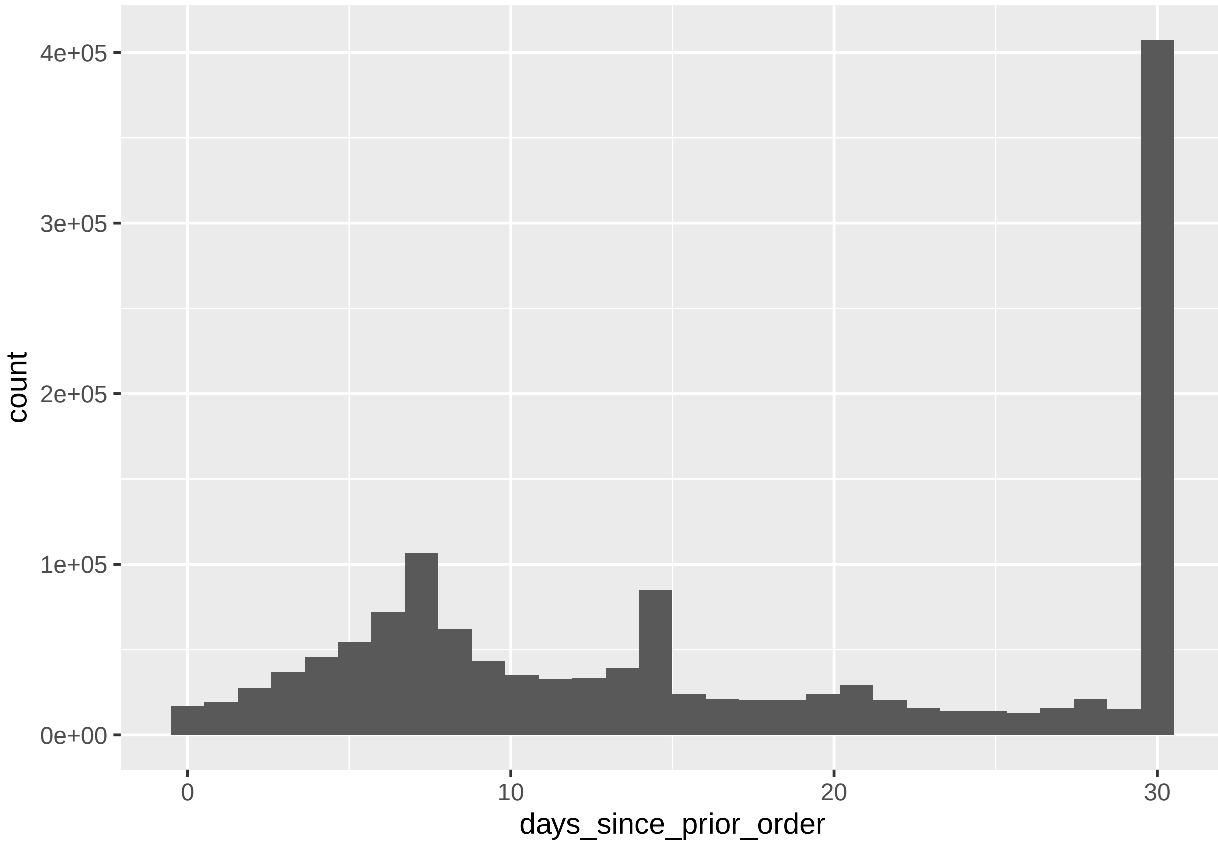



```
#Sunday, Monday and Saturday appear to be the most common days where people place their orders.
```

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

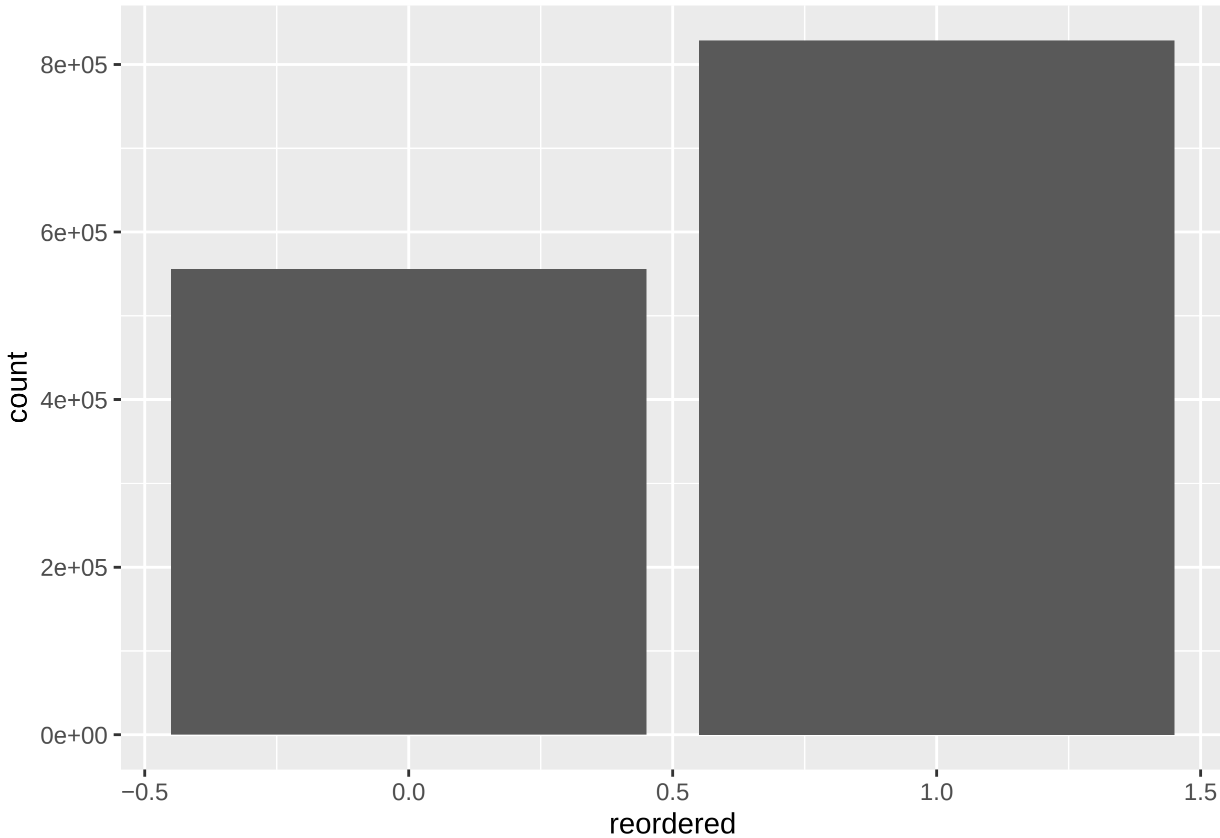
```
X %>% ggplot(aes(x=days_since_prior_order))+
      geom_histogram()
```

```
## `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))
```



Find the percentage of transactions from the top 10 products sold.

```
X %>%
  group_by(product_name) %>%
  dplyr::summarize(count =n()) %>%
  mutate(pct=(count/sum(count))*100) %>%
  arrange(desc(pct)) %>%
  ungroup() %>%
  top_n(10, wt=pct)
```

```
## # A tibble: 10 x 3
##    product_name           count   pct
##    <fct>                  <int> <dbl>
##  1 Banana                 18726 1.35
##  2 Bag of Organic Bananas 15480 1.12
##  3 Organic Strawberries   10894 0.787
##  4 Organic Baby Spinach    9784 0.707
##  5 Large Lemon             8135 0.588
##  6 Organic Avocado         7409 0.535
##  7 Organic Hass Avocado    7293 0.527
##  8 Strawberries            6494 0.469
##  9 Limes                   6033 0.436
## 10 Organic Raspberries     5546 0.401
```

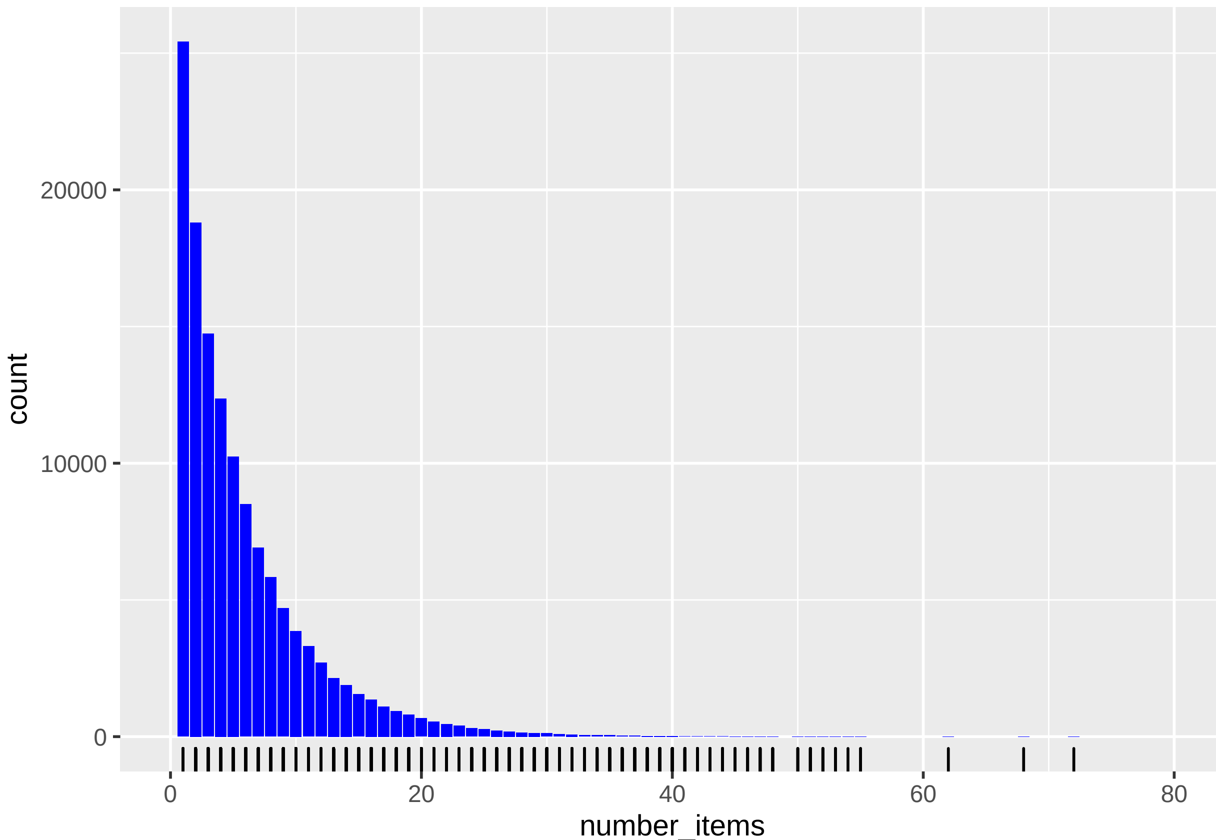
Top 10 products sold and the percentage of transactions they are involved in. Bananas make up 1.35% of the transactions, while organic bananas make up 1.1% of the transactions and organic strawberries make up

0.79% of the transactions.

How many items are in each transaction?

```
X %>%
  group_by(order_id) %>%
  dplyr::summarise(number_items=last(add_to_cart_order)) %>%
  ggplot(aes(x=number_items)) +
  geom_histogram(stat="count", fill="blue") +
  geom_rug()+
  coord_cartesian(xlim=c(0,80))
```

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



Items most often reordered:

```
reordered <- X %>%
  group_by(product_name) %>%
  dplyr::summarize(proportion_reordered = mean(reordered), n=n()) %>%
  filter(n>40) %>%
  top_n(10, wt=proportion_reordered) %>%
  arrange(desc(proportion_reordered))

kable(reordered)
```

product_name	proportion_reordered	n
2% Lactose Free Milk	0.9347826	92
Organic Low Fat Milk	0.9130435	368
100% Florida Orange Juice	0.8983051	59
Organic Spelt Tortillas	0.8888889	81
Original Sparkling Seltzer Water Cans	0.8888889	45
Banana	0.8841717	18726
Petit Suisse Fruit	0.8833333	120
Organic Lowfat 1% Milk	0.8819876	483
Organic Lactose Free 1% Lowfat Milk	0.8810409	269
1% Lowfat Milk	0.8785249	461

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

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

rename column to items

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

write the transaction data csv into a csv file:

```r
#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

```r
tr
```

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

```r
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

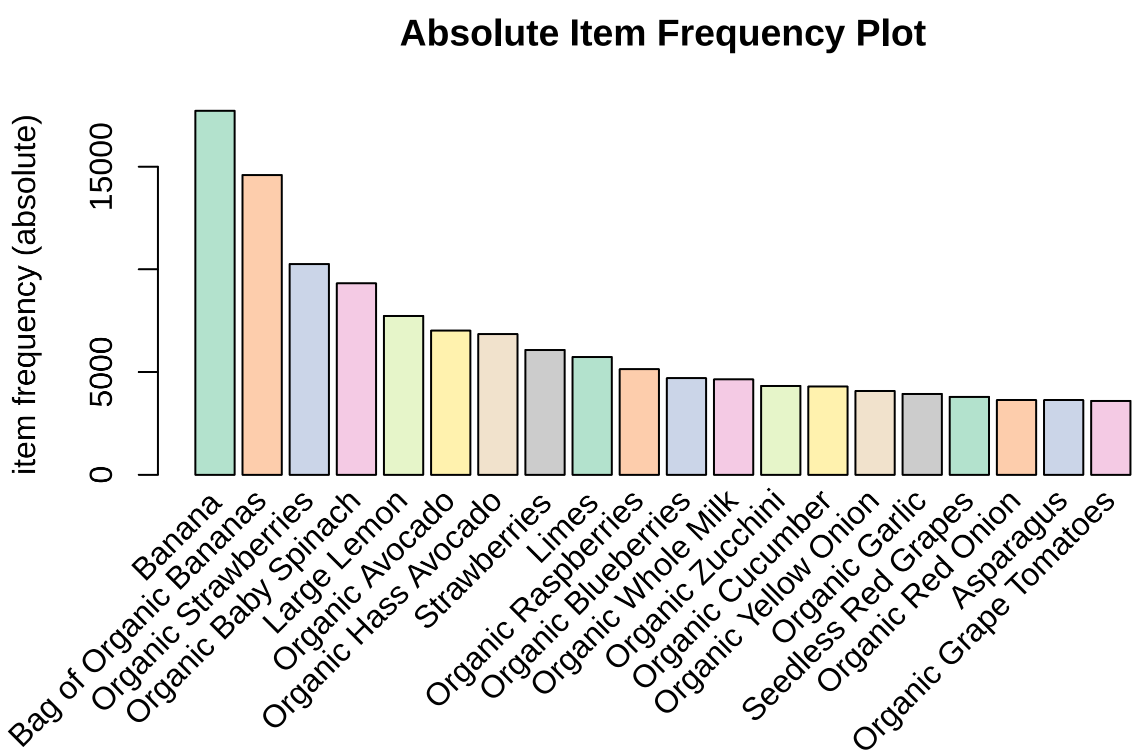
A sparse matrix is a matrix in which most elements are zero.

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
```

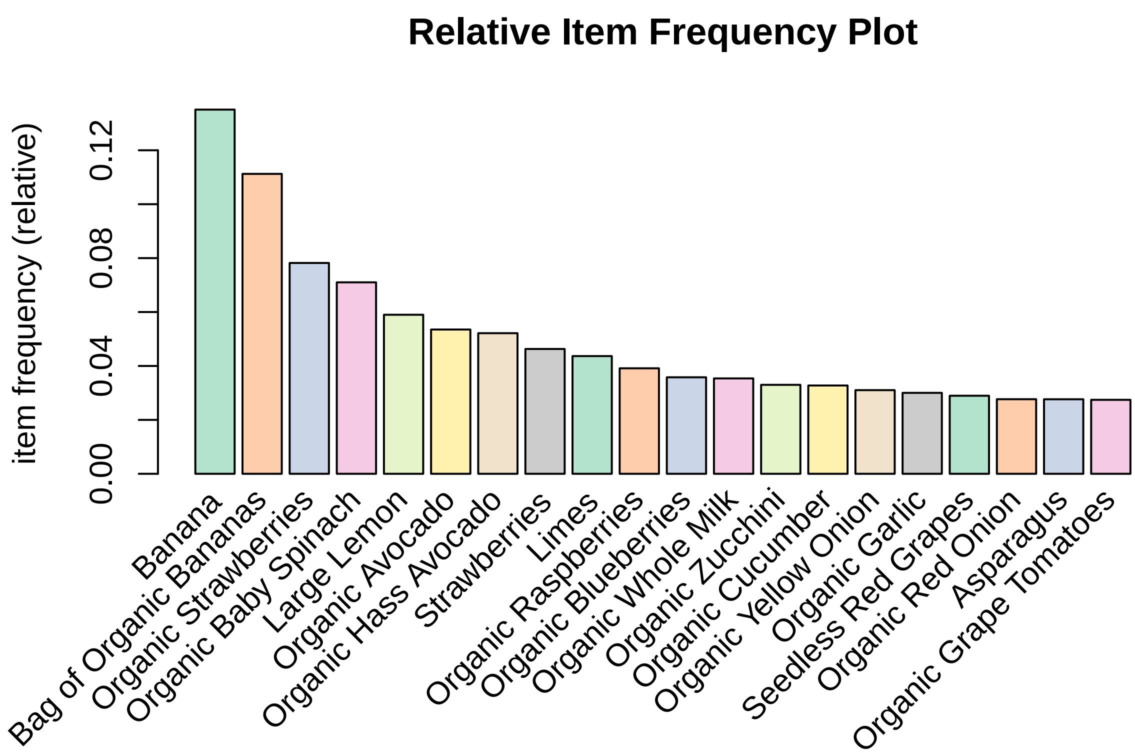


According to the frequency plot, the top 20 products bought in Instacart are banana, bag of organic bananas, organic strawberries, organic baby spinach, large lemon, organic avocado, organic hass avocado, strawberries, limes, organic raspberries, organic blueberries, organic whole milk, organic zucchini, 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):

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



Generating Rules

Mine the rules using APRIORI algorithm.

```r
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 [0.95s].
## sorting and recoding items ... [1812 item(s)] done [0.02s].
## creating transaction tree ... done [0.07s].
```

```
## checking subsets of size 1 2 3 4 done [0.07s].
## 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).

```r
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:

```r
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 [0.86s].
## sorting and recoding items ... [1812 item(s)] done [0.02s].
## 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 [0.03s].
```

```
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

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

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

```r
#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:

```r
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:

```r
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 [0.83s].
## sorting and recoding items ... [1812 item(s)] done [0.03s].
## creating transaction tree ... done [0.08s].
## checking subsets of size 1 2 3 4 done [0.07s].
## writing ... [3 rule(s)] done [0.00s].
## creating S4 object  ... done [0.02s].
```

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

```r
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 [0.89s].
## sorting and recoding items ... [1812 item(s)] done [0.03s].
## creating transaction tree ... done [0.07s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [2 rule(s)] done [0.00s].
## creating S4 object  ... done [0.02s].
```

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))
```

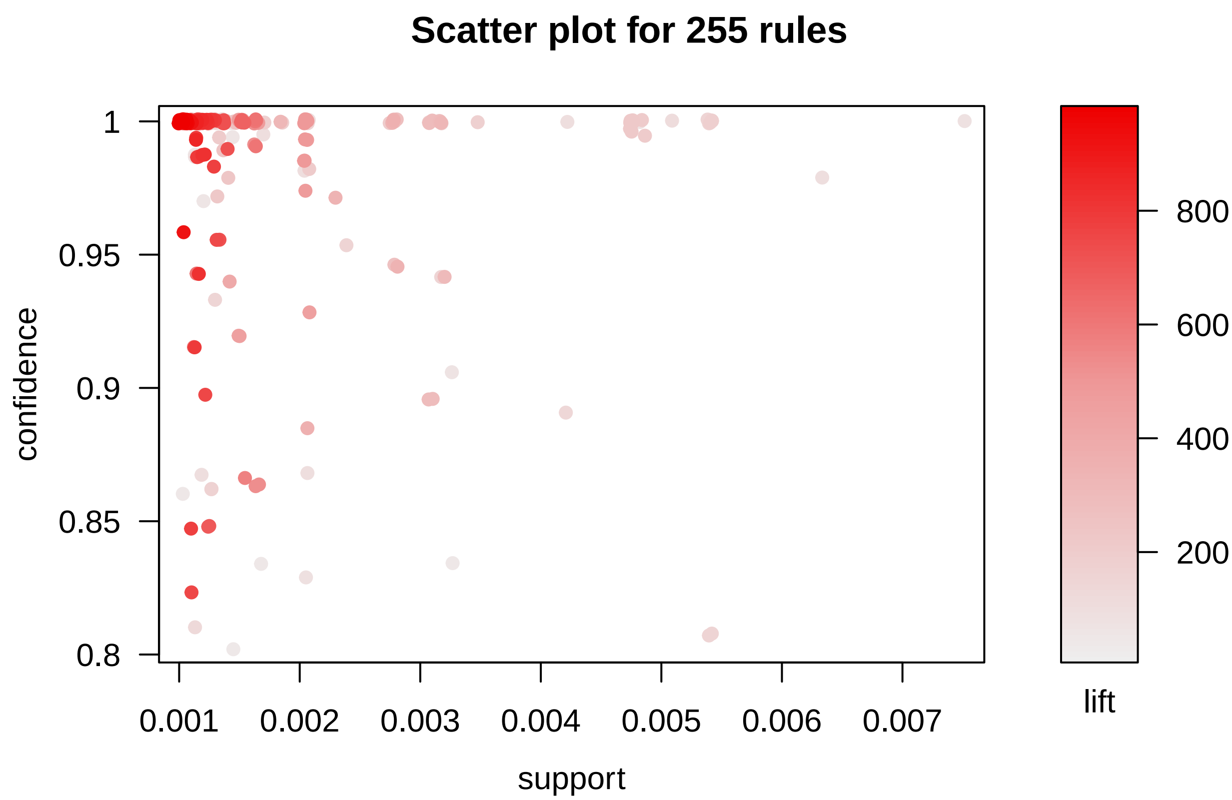
```
##     lhs                   rhs            support     confidence coverage
## [1] {French Baguettes} => {Take & Bake} 0.001021264 1          0.001021264
## [2] {French Baguettes} => {Twin Pack}   0.001021264 1          0.001021264
##     lift     count
## [1] 979.1791 134
## [2] 979.1791 134
```

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.
```

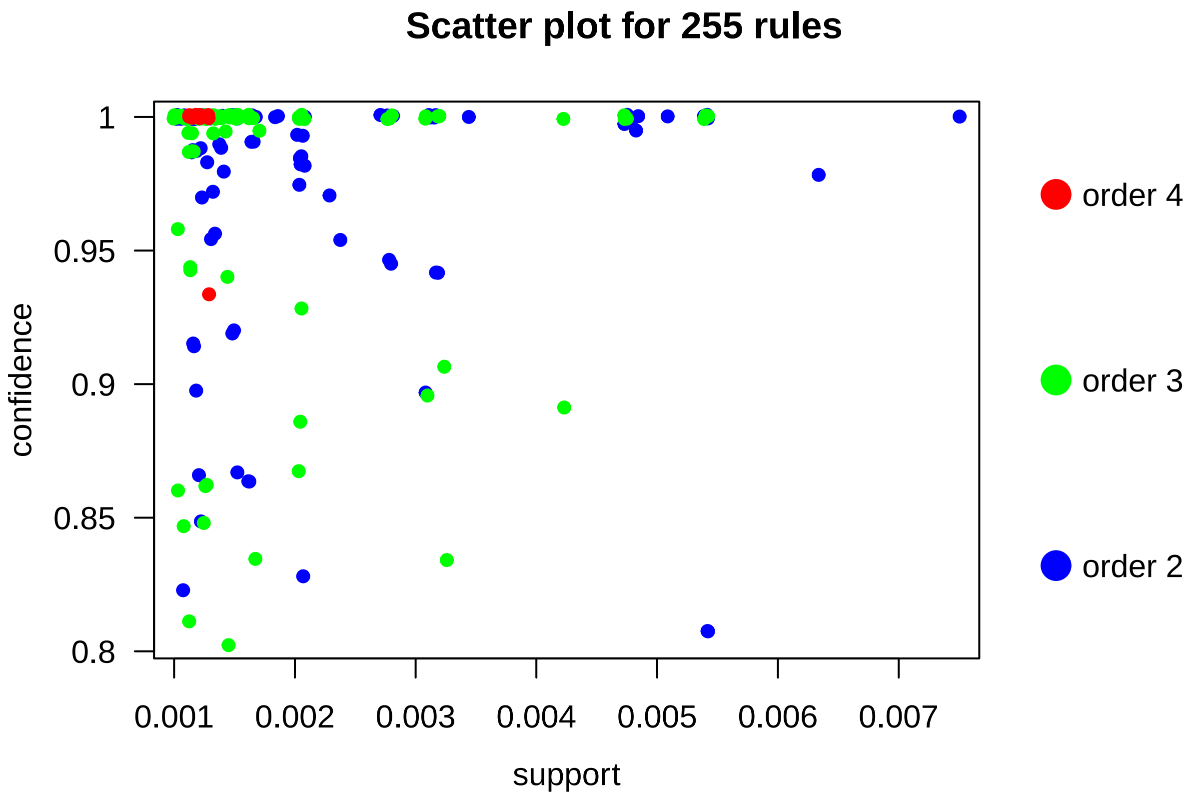


Rules with high lift have low support

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.
```



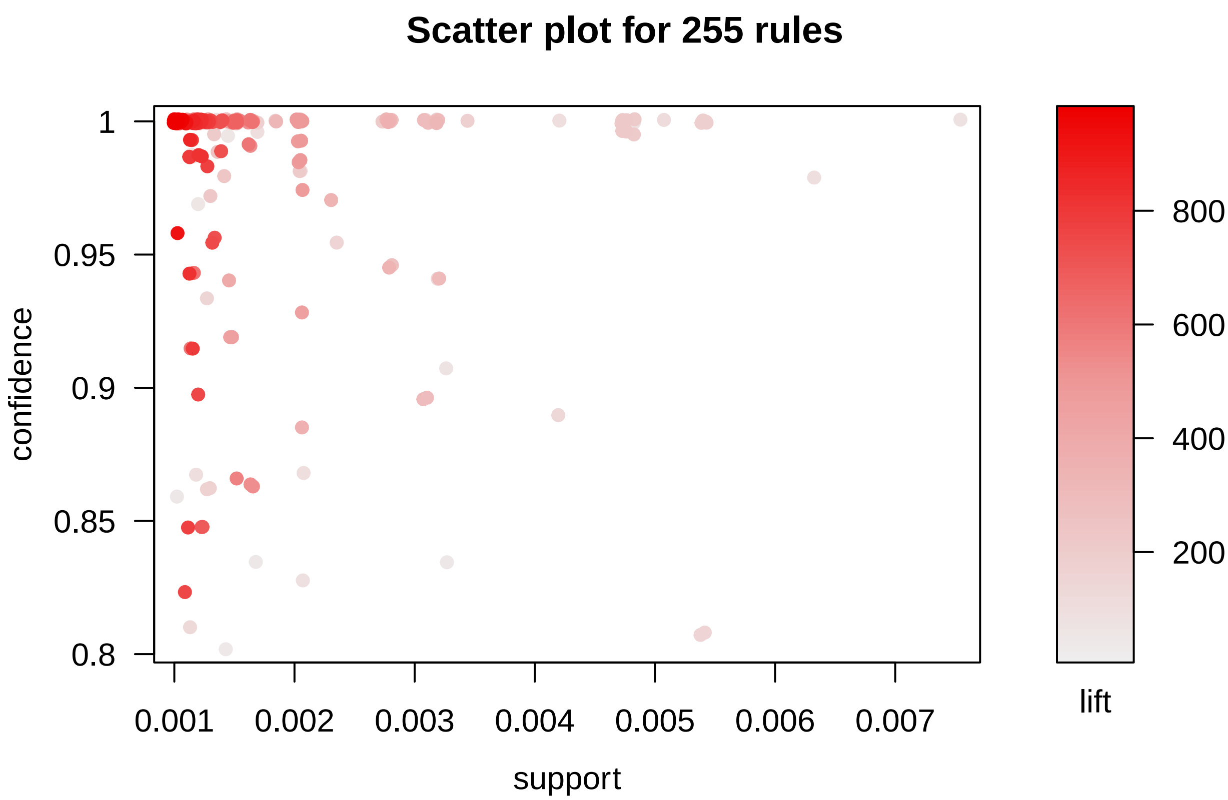
Two key plot has support on x axis and confidence on y-axis. It uses order for coloring. Order is the number of items in the rule.

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.
```



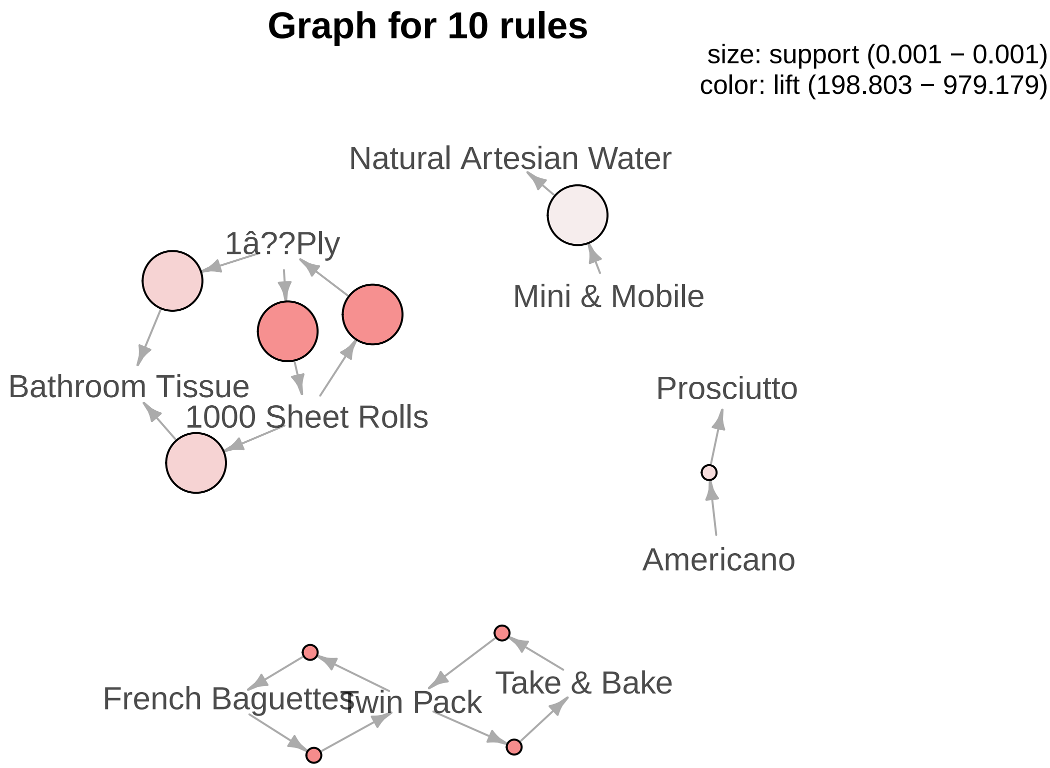
Graph based methods: vertices are labeled with item names; item sets or rules are indicated with a second set of vertices: arrows point from items to rule vertices = LHS; arrow from rule to an item = RHS. Size & color = interest measure.

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")
```



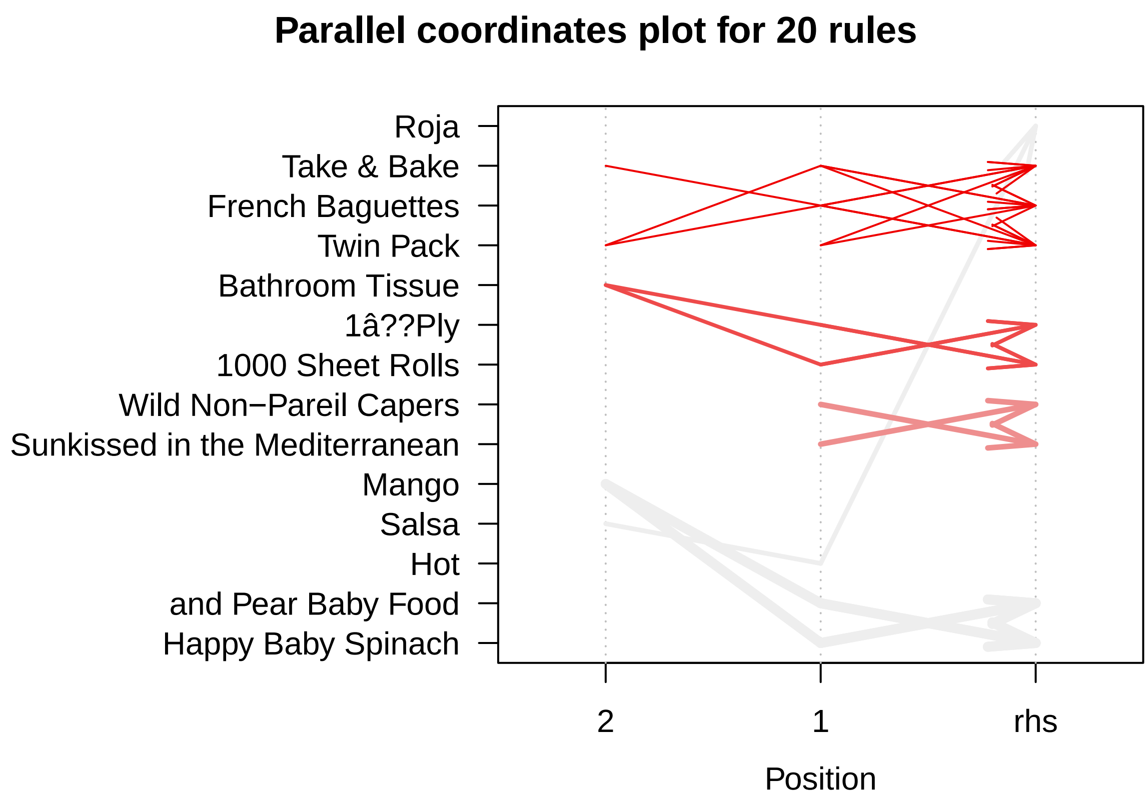
To export graphs for sets of association rules in GraphML format (which you can open with Gephi tool):

```
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.

Recommender Method 2: Weighted Alternating Least Squares with Implicit Feedback Data

```
#Extract columns for matrix
transactions<-X[,c("user_id","product_id","order_id")]

#selecting 8K users for modeling
all_users<-unique(transactions$user_id)
randm_users<-sample(all_users,8000L)

#selecting 16K products
all_products<-unique(transactions$product_id)
rand_products<-sample(all_products,16000L)



#final data for matrix
interactions<-transactions %>%
                     filter(user_id %in%randm_users & product_id %in%rand_products)

#find the total orders for each user per product
```

```r
interactions_sample<-interactions %>%
  group_by(user_id,product_id) %>%
  dplyr::summarise(orders=n())
```

```
## `summarise()` has grouped output by 'user_id'. You can override using the `.groups` argument.
```

```r
#encoding users and products
user_enc <-  interactions_sample %>%
  distinct(user_id) %>%
 rowid_to_column()

names(user_enc)[names(user_enc) == "rowid"]<- "uid_enc"

product_enc<- interactions_sample %>%
  distinct(product_id)  %>%
 rowid_to_column()

names(product_enc)[names(product_enc) == "rowid"]<- "pid_enc"
```

```r
#sparse matrix
data<-interactions_sample %>%
  inner_join(user_enc, by = 'user_id') %>%
  inner_join(product_enc, by = 'product_id')



X = sparseMatrix(i = data$uid_enc, j = data$pid_enc, x = data$orders,
                 dimnames = list(user_enc$user_id, product_enc$product_id))
```

```r
#test set

n_test <- 2000L
test_uid <- sample(nrow(user_enc), n_test)

X_train <-  X[-test_uid, ]
X_test <-  X[test_uid, ]
```

```r
# Split our test set into "history" or "future"
temp = as(X_test, "TsparseMatrix")
temp = data.table(i = temp@i, j = temp@j, x = temp@x)



temp <- temp %>%
  group_by(i) %>%                        # group by user
  mutate(ct = length(j),                 # number of products each user has
         history =
           sample(c(TRUE, FALSE), ct, replace = TRUE, prob = c(.5, .5))) %>%
  select(-ct)


X_test_history <- temp %>% filter(history == TRUE)
```

```r
X_test_future <- temp %>% filter(history == FALSE)




X_test_history <- sparseMatrix(i = X_test_history$i,
                               j = X_test_history$j,
                               x = X_test_history$x,
                               dims = dim(X_test),
                               dimnames = dimnames(X_test),
                               index1 = FALSE)




X_test_future <- sparseMatrix(i = X_test_future$i,
                              j = X_test_future$j,
                              x = X_test_future$x,
                              dims = dim(X_test),
                              dimnames = dimnames(X_test),
                              index1 = FALSE)
```

```r
#  confidence functions and create matrices

lin_conf <- function(x, alpha) {
  x_confidence <- x
  stopifnot(inherits(x, "sparseMatrix"))
  x_confidence@x = 1 + alpha * x@x
  return(x_confidence)
}
```

```r
alpha <- .1
lambda <- 10
components <- 10L

#factor matrices for train and test

X_train_conf <- lin_conf(X_train, alpha)
X_test_history_conf <- lin_conf(X_test_history, alpha)
```

```r
# Initialize a model
# Define hyper parameters
#rank=the number of latent factors in the model (defaults to 10)
#value of alpha is calculated using cross validation






model <- WRMF$new(rank = components,
                  lambda = lambda,
                  feedback = 'implicit',
                  solver = 'conjugate_gradient')
```

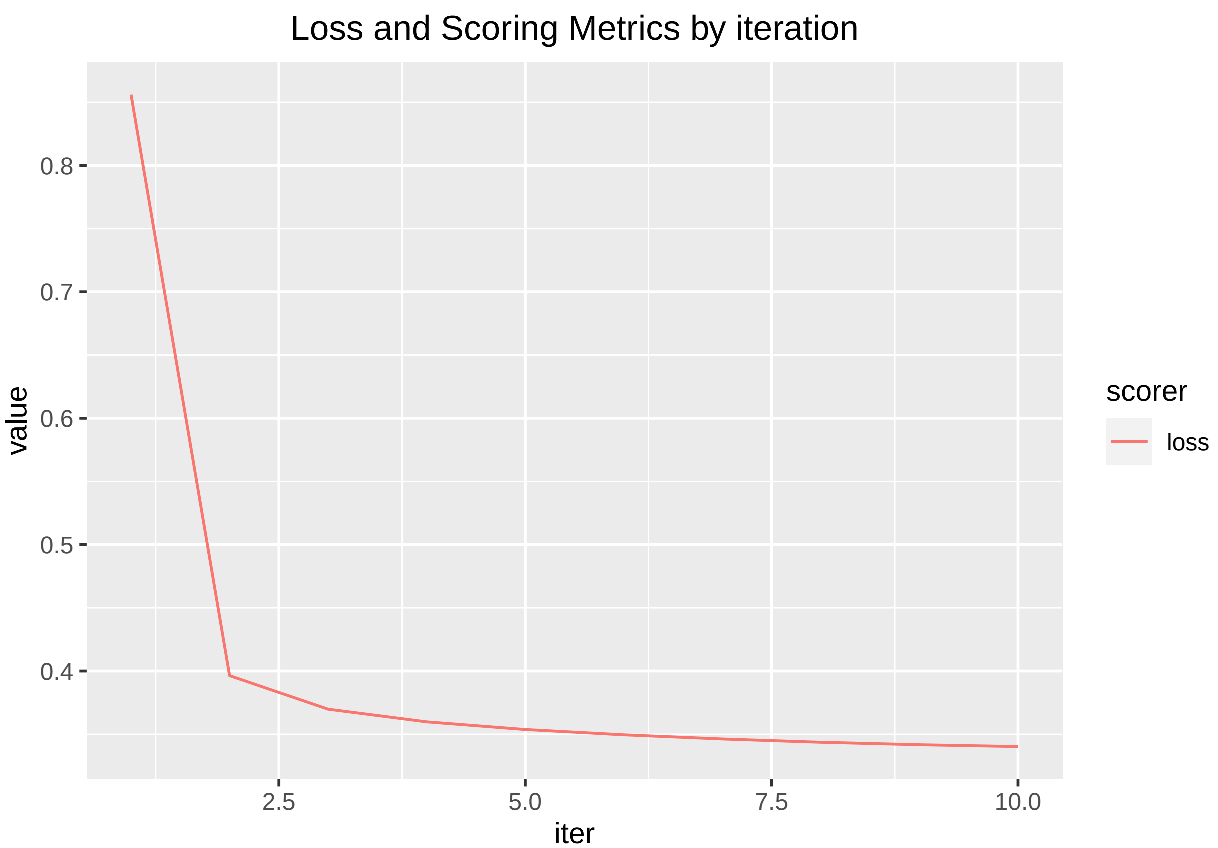
```r
# Calculate user factors
train_user_factors <- model$fit_transform(X_train_conf)
```

```
## INFO  [21:48:23.388] starting factorization with 8 threads
## INFO  [21:48:23.509] iter 1 loss = 0.8560
## INFO  [21:48:23.621] iter 2 loss = 0.3963
## INFO  [21:48:23.712] iter 3 loss = 0.3698
## INFO  [21:48:23.813] iter 4 loss = 0.3598
## INFO  [21:48:23.918] iter 5 loss = 0.3537
## INFO  [21:48:24.020] iter 6 loss = 0.3495
## INFO  [21:48:24.111] iter 7 loss = 0.3462
## INFO  [21:48:24.210] iter 8 loss = 0.3436
## INFO  [21:48:24.309] iter 9 loss = 0.3417
## INFO  [21:48:24.403] iter 10 loss = 0.3402
## INFO  [21:48:24.403] Converged after 10 iterations
```

```r
# Products matrix and recommendations are  made by selecting the top 10  items for which P(ui) is great

test_predictions <- model$predict(X_test_history_conf, k = 10)


#Loss and Score or fixed product factors
trace = attr(train_user_factors, "trace")
ggplot(trace) +
  geom_line(aes(x = iter, y = value, col = scorer)) +
  labs(title = "Loss and Scoring Metrics by iteration") +
  theme(plot.title = element_text(hjust = .5))
```



Recommenderlab for Evaluation of Different Recommender Algorithms in R

Using Recommederlab in R: 2 types of rating matrix for modelling is available; we will be using the binary rating matrix type where 0 indicates product is not purchased, while 1 indicates product is purchased.

Binary rating matrix is useful when no actual user ratings is available, and it also does not require normalisation.

The rating matrix must be rearranged with orders in rows and products in columns.

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

```
# train users for top 50

train_users<- X %>%
  filter(product_id %in% top_products_train$product_id) %>%
 group_by(user_id,product_id, .groups='keep') %>%
  dplyr::summarise(tot=n()) %>%
  ungroup() %>%
  group_by(user_id) %>%
  dplyr::summarise(count2=n()) %>%
 arrange(desc(count2))
```

```
## `summarise()` has grouped output by 'user_id', 'product_id'. You can override using the `.groups` ar
```

```
View(train_users)
```

#transaction for top 50 products (train)

```
train_top_50 <- X %>%
filter(user_id %in%train_users$user_id  & product_id %in% top_products_train$product_id)
```

```
dim(train_top_50)
```

```
## [1] 225084     16
```

Check if products are ordered multiple times within the same transaction:

```
retail <- train_top_50 %>%
  #create a unique identifier for each product in a transaction using the order id and product name inf
  mutate(orderID_product = paste(order_id, product_name, sep=' '))
#225084 entries
```

```
#filter out duplicates and drop unique identifier
retail <- retail[!duplicated(retail$orderID_product), ] %>%
  select(-orderID_product)
#still 225084 entries, so customers generally do not buy multiples of a single product within the same
```

```
ratings_matrix <- retail %>%
  select(order_id, product_name) %>%
  mutate(value=1) %>%                         #add a column of 1s
  spread(product_name, value, fill=0) %>%     #spread into user-item format
  select(-order_id) %>%
  as.matrix() %>%
  as("binaryRatingMatrix")                    #convert to recommenderlab class binary matrix

ratings_matrix
```

```
## 81751 x 50 rating matrix of class 'binaryRatingMatrix' with 225084 ratings.
```

Evaluation scheme and Model validation

Evaluate the model's effectiveness using recommenderlab's evaluation schemes.

Split the data into a training set and test set with train taking 80% of the data and test taking 20% of the data.

Set method="cross" and k=5 for 5 fold cross-validation. Data will be split into k subsets of equal size, and 80% of data will be used for training and last 20% for evaluation. Models are then estimated recursively 5 times, and a different train/test split is used each time. Results are then averaged to produce a single evaluation set.

```
scheme <- ratings_matrix %>%
  evaluationScheme(method="cross",
                   k = 5,
                   train = 0.8,
```

```
                    given = -1)   #selecting given = -1 means that for the test users 'all but 1" random

scheme
```

```
## Evaluation scheme using all-but-1 items
## Method: 'cross-validation' with 5 run(s).
## Good ratings: NA
## Data set: 81751 x 50 rating matrix of class 'binaryRatingMatrix' with 225084 ratings.
```

Set up a list of algorithms

Create a list of algorithms from recommenderlab and specify model parameters. Consider schmemes which evaluate on the binary rating matrix and include random items algorithm for benchmarking.

```
algorithms <- list(
  "association rules" = list(name = "AR",
                             param = list(supp=0.001, conf=0.01)),
  "random items"  = list(name = "RANDOM", param=NULL),                #randomly chosen items for compar
  "popular items" = list(name = "POPULAR", param = NULL),             #recommender based on item popula
  "item-based CF" = list(name = "IBCF", param = list(k=5))           #recommender based on item-based c
  #"user-based CF" = list(name = "UBCF",                               #recommender based on user-based
  #                      param = list(method = "Cosine", nn= 50))      #user-based CF often runs into m
  )
```

Pass the scheme and algorithms to the evaluate() function, to evaluate several recommender algorithms using an evaluation scheme. The end product is a evaluation result list.

elect type= topNList to evaluate a Top N List of product recommendations and specify how many recommendations to calculate with the parameter n = c(1,3,5,10,15,20)

Note: for the UBCF method, it is important to allocate enough memory in RStudio for processing.

To check the current limit in R session use memory.limit(); and then to increase the size of memory use memory.limit(size=n) ie. memory.limit(size=56000)

```
#run garbage collection to free up memory for analysis:
gc()
```

```
##            used  (Mb) gc trigger  (Mb)  max used  (Mb)
## Ncells  4064360 217.1    8570511 457.8   8570511 457.8
## Vcells 60037242 458.1  110362426 842.0 109805462 837.8
```

```
#remove from global environment variables which are not needed for the analysis:
# rm(X, transactionData, train_users, tr, top10subRules, top_products_train, subset.association.rules, 


#change memory limit to 56000 Mb to prevent problems with memory limit ("cannot allocate vector of size
memory.limit(size=56000)
```

```
## [1] 56000
```

```r
results <- recommenderlab::evaluate(scheme,
                                    algorithms,
                                    type= "topNList",
                                    n = c(1,3,5,10, 15, 20))
```

```
## AR run fold/sample [model time/prediction time]
##   1  [0.06sec/183.7sec]
##   2  [0.04sec/231.36sec]
##   3  [0.08sec/199.95sec]
##   4  [0.05sec/216.98sec]
##   5  [0.06sec/202.99sec]
## RANDOM run fold/sample [model time/prediction time]
##   1  [0sec/1.68sec]
##   2  [0sec/1.8sec]
##   3  [0sec/1.81sec]
##   4  [0sec/2.06sec]
##   5  [0sec/1.85sec]
## POPULAR run fold/sample [model time/prediction time]
##   1  [0.02sec/12.18sec]
##   2  [0.01sec/11.52sec]
##   3  [0sec/10.57sec]
##   4  [0.02sec/11.1sec]
##   5  [0sec/14.23sec]
## IBCF run fold/sample [model time/prediction time]
##   1  [0.23sec/1.9sec]
##   2  [0.33sec/1.28sec]
##   3  [0.21sec/1.49sec]
##   4  [0.24sec/1.29sec]
##   5  [0.2sec/1.52sec]
```

```r
results
```

```
## List of evaluation results for 4 recommenders:
##
## $`association rules`
## Evaluation results for 5 folds/samples using method 'AR'.
##
## $`random items`
## Evaluation results for 5 folds/samples using method 'RANDOM'.
##
## $`popular items`
## Evaluation results for 5 folds/samples using method 'POPULAR'.
##
## $`item-based CF`
## Evaluation results for 5 folds/samples using method 'IBCF'.
```

```r
names(results)
```

```
## [1] "association rules" "random items"      "popular items"
## [4] "item-based CF"
```

```r
#Access individual results by list subsetting using an index or the name specified when calling evaluat
results[["item-based CF"]]
```

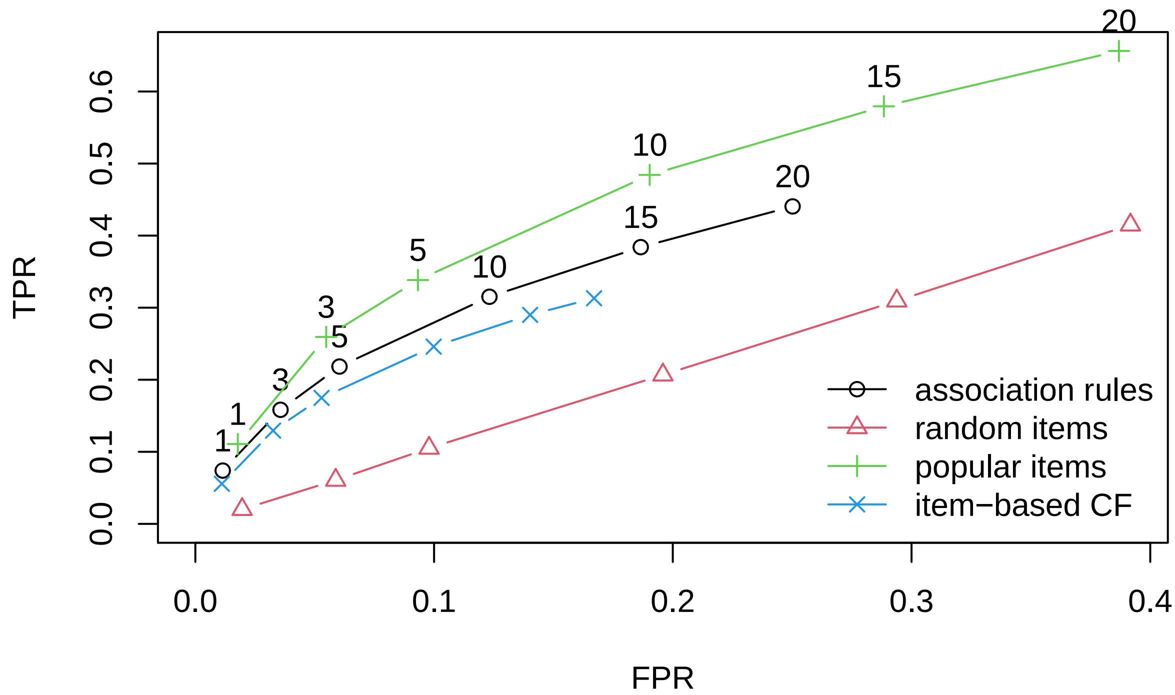
```
## Evaluation results for 5 folds/samples using method 'IBCF'.
```

Visualise the Results

Use plot function from recommenderlab to compare model performance

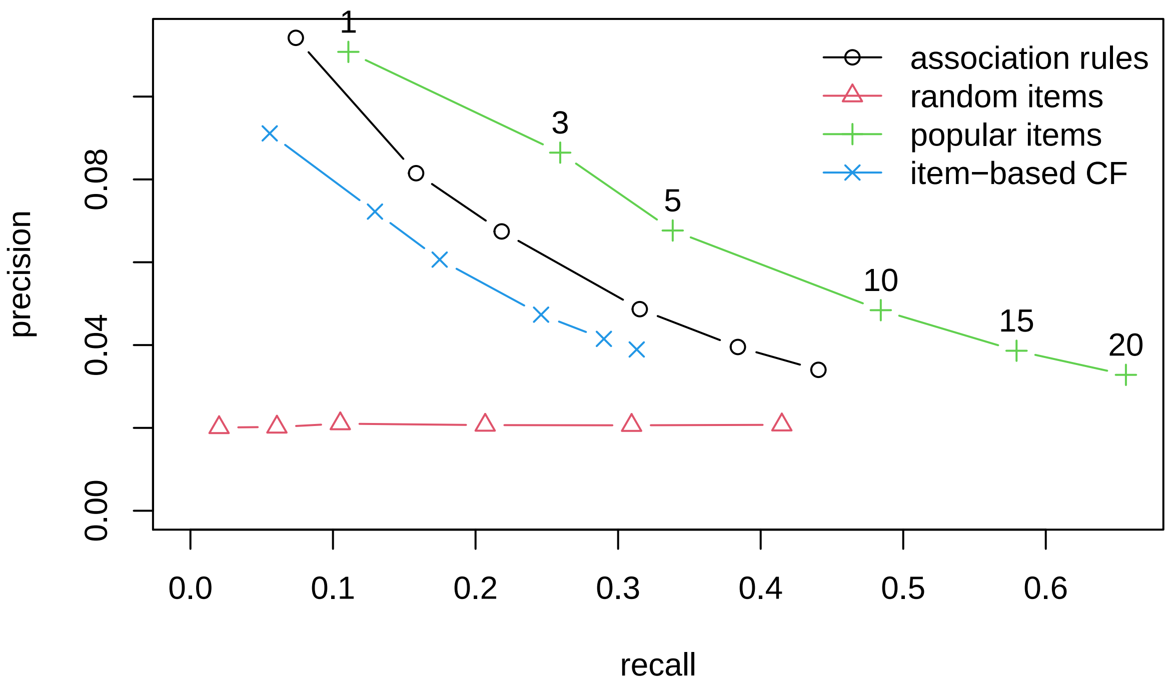
Arrange confusion matrix for one model in a convenient format:

```r
plot(results, annotate=c(1,3), legend="bottomright")
```



Comparison of ROC curves. For this datset and the given evaluation scheme, popular items and association rules outperform the other methods, in providing a better combination of TPR and FPR amongst the 4 alogorithms evaluated for the top-N list recommendations.

```r
plot(results, "prec/rec", annotate=3, legend="topright")
```



Comparison of precision vs. recall curves for the 4 recommender algorithms shows that Popular items and association rules performed the best for the given evaluation scheme.

References

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