# ML1000 Assignment 3 - Recommender System using Apriori Algorithm and Weighted Alternating Least Squares with Implicit Feedback

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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, purchase histor the users, comparison with other products, and so on, before making recommendations. Many industry leaders have started using implicit data for recommendation systems.

We built two main recommender systems using the Instacart Online Grocery Shopping Dataset 2017. The first recommender system uses the APRIORI algorithm to mine for patterns between items which are frequently bought together. The results of the APRIORI method identifies association rules between different products, so that if a customer has a certain item in their basket, other frequently bought items will be suggested.

The second recommender system we built is using Weighted Alternating Least Squares with Implicit Feedback Data (WALSIFD). In the WALSIFD method, if a customer bought an item several times, it is assumed that there is positive feedback in terms of user preference for those items. The objective of this model is to identify products that has a high probability of being clicked on or purchased by a user, based on their previous transactions.

## Business Understanding

Instacart is a large retail grocery chain with a large online presence. Their website has millions of visitors.The website lists hundreds of thousands of unique products. Management thinks consumers faced with too many options are simply avoiding decision making due to too many choices.This is described as a decline in decision making over long sessions also called decision fatigue. The management is looking for a solution to convert more of these visitors into buyers. They also want to increase sales to existing customers. They have enlisted our team to implement this solution with a requirement to improve sales and improve customer satisfaction. Instacart is aiming to recommend items that are very likely to be bought together with the other groceries that the customers are interested in, based on the associations that items are bought together, based on customers' past purchasing history. By making recommendations, customers' shopping time could be reduced, and they can find the items they intend to buy or relevant products more easily, without the need to browse through many pages to look for one item. Also, when the customers see the recommended frequently bought items, it increases the likelihood of them buying more groceries, which will improve Instacart's sales as well. Instacart can also provide a personalized shopping experience using the recommender system by promoting the items that a customer buys regularly.

Our client is looking to implement a recommender system that can give customers suggestions for additional products based on their previously purchased products. Another requirement of the recommender system requested is to be able to provide recommendations on other products based on the items already in a customer's basket. For this part of the recommender system, the machine learning model will predict or suggest an item which is frequently bought with items that are already in a customer's basket. The recommender model predicts items which have a high probability of being ordered by a user, due to being frequently bought together with items already in the order basket. Recommendations provided by the model will enable users to save time in remembering to add items to their basket, or provide suggestions for products likely to be suitable for that customer, based on their previous purchases.

## Objective

The primary goals of the project will be to calculate the similarity between items and frequently bought items. We identified the goal as simplifying the choices for existing customers and thereby improve customer satisfaction and drive more online sales. Our solution is to provide a product recommendation system. The recommender will suggest new products to buyers based on two methods. This will help drive more business on the website of the retailer and increase profitability. Collaborative filtering using Matrix Factorization and Weighted ALS is one of the approaches used by the recommended algorithm. Apriori is used for finding frequently bought items.

## Ethical Machine Learning Framework

The Instacart Online Grocery Shopping dataset does not contain identifiable information for the users who made the transactions. User data does not contain any customer names, only anonymous user ids are included, which helps to maintain privacy of Instacart customers. Transaction data also does not include any sensitive information such as postal code. The current data set do not contain any information about gender or ethnicity, so this information will not have any influence on the recommendations predicted by the recommender systems. The Instacart R Shiny app is hosted on Shinyapps.io which is secure by design, where the application will run on its own protected environment, and access is SSL encrypted (RStudio, 2020). Only writers of the Instacart recommendation app is able to modify the code for the application, because user authentication is required for login to the shinyapps.io site where the application is hosted.

## Data Understanding

The "Instacart Online Grocery Shopping Dataset 2017" was obtained from https://www.kaggle.com/c/instacart-market-basket-analysis/data The dataset is anonymized and contains a total of 3 million grocery orders from more than 200,000 Instacart users. For each user, 4 to 100 of their orders was included in the data, including the sequence in which customers purchased products for each order. Other information in the dataset include the day of week the transaction occurred, time between orders, product name, product id, grocery aisle information, and whether products were reordered. The dataset was originally collected by Instacart for use as a public dataset for machine learning. The dataset can be used to create and test models to predict which products are likely to be re-ordered by a user, ordered for the first time or added to the cart next in a transaction (Stanley, 2017).

### How did 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.

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. Added 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.

## Data Preparation

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 ...
```

```r
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[,]

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

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

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

No missing values in dataset.

look at first 10 rows of dataset

```r
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
```

To examine some of the statistics of the dataset:

```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"
```

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

How many unique orders are in the training dataset?

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

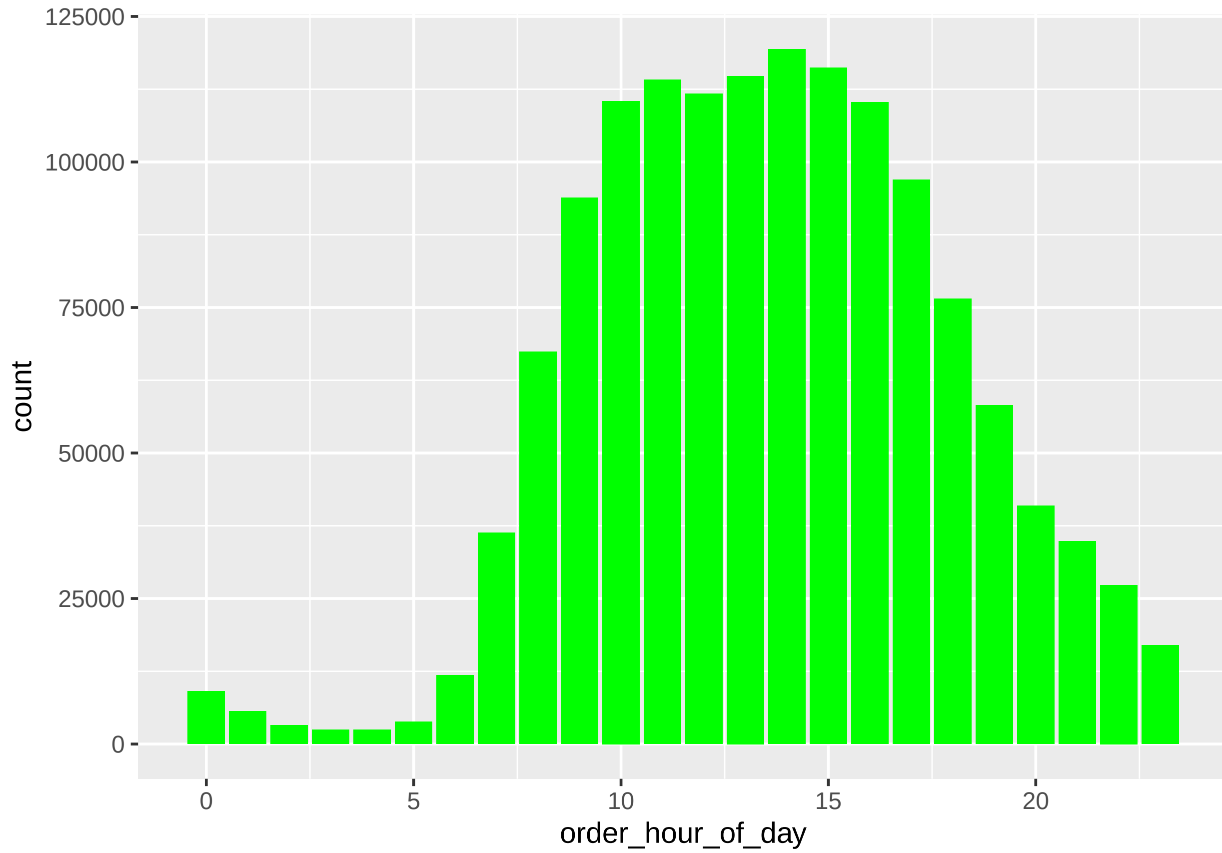
```
## [1] 131209
```

Recode order_hour_of_day to numeric:

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

What times are orders placed?

```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()) %>%
```

```r
  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))
```

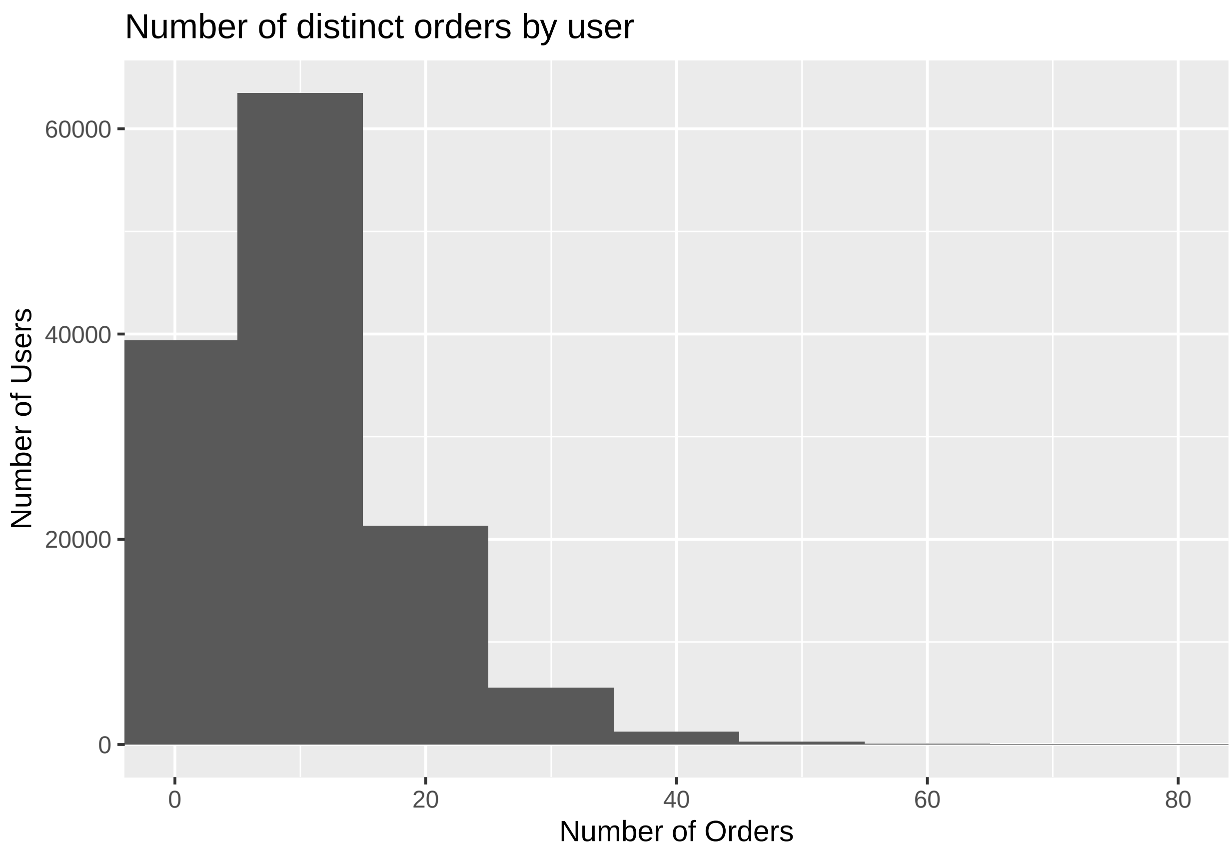



Figure 1: Bar chart of number of distinct orders by user. Most users (around 65000) have 10 distinct orders. The next biggest group of users (40000) have between 0 -10 distinct orders placed.

Number of distinct products per user:

```r
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.
```

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

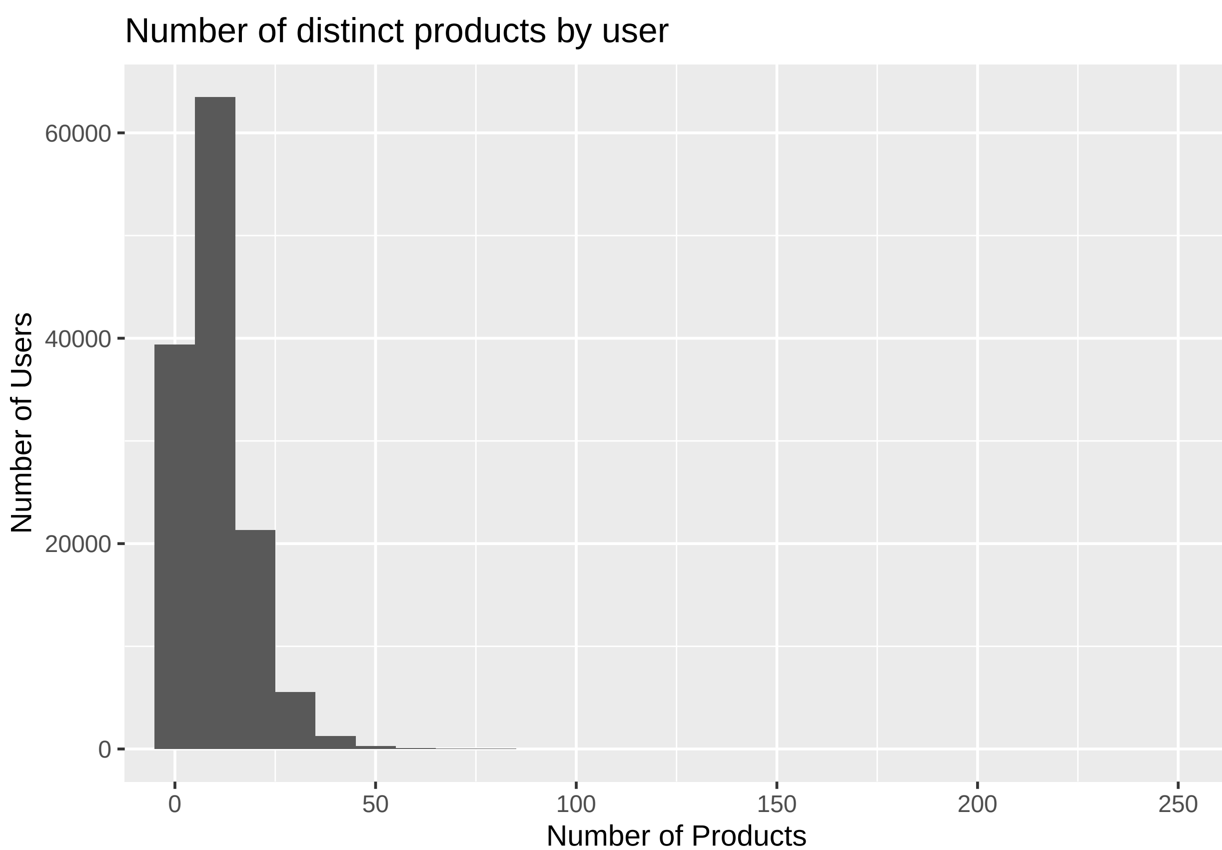


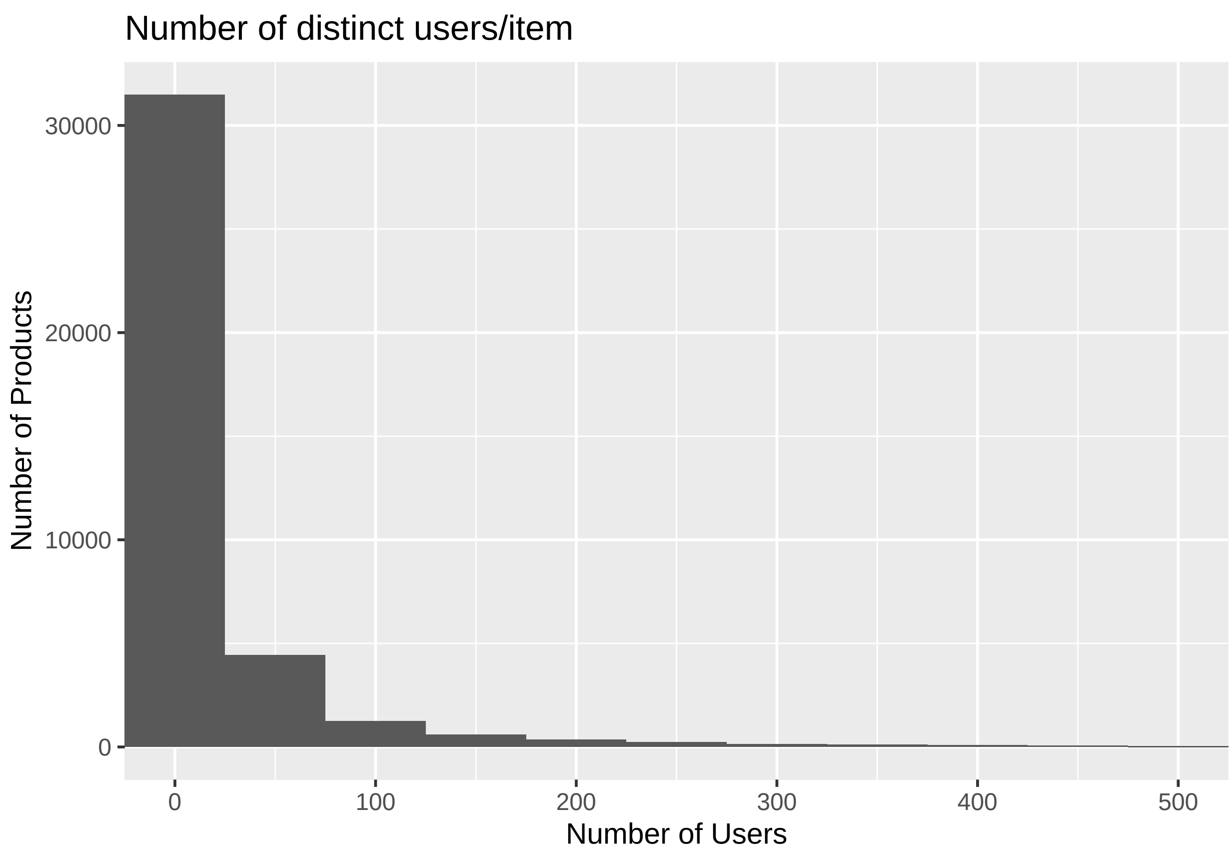

Figure 2: Bar chart of number of distinct products by user for training orders

Number of distinct users/item

```r
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()
```

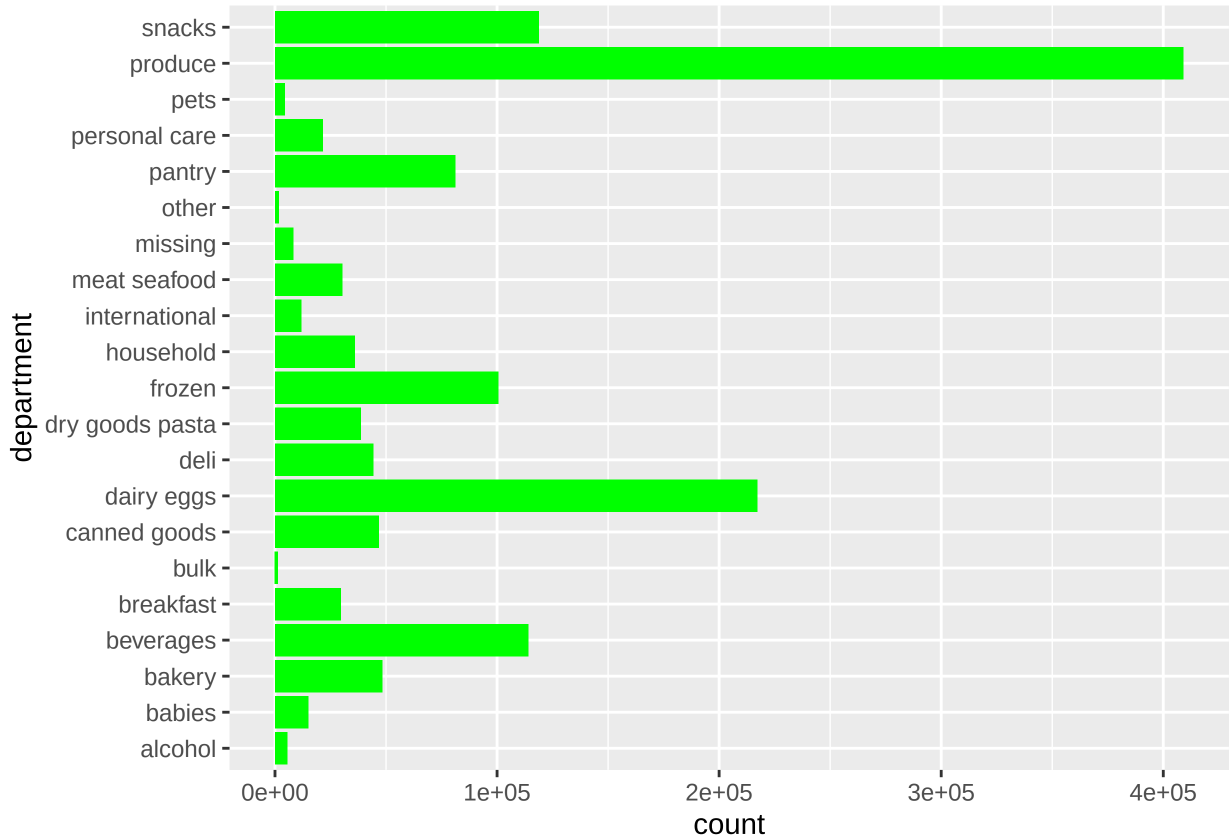
```
## `summarise()` has grouped output by 'product_id'. You can override using the `.groups` argument.
```

```r
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

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

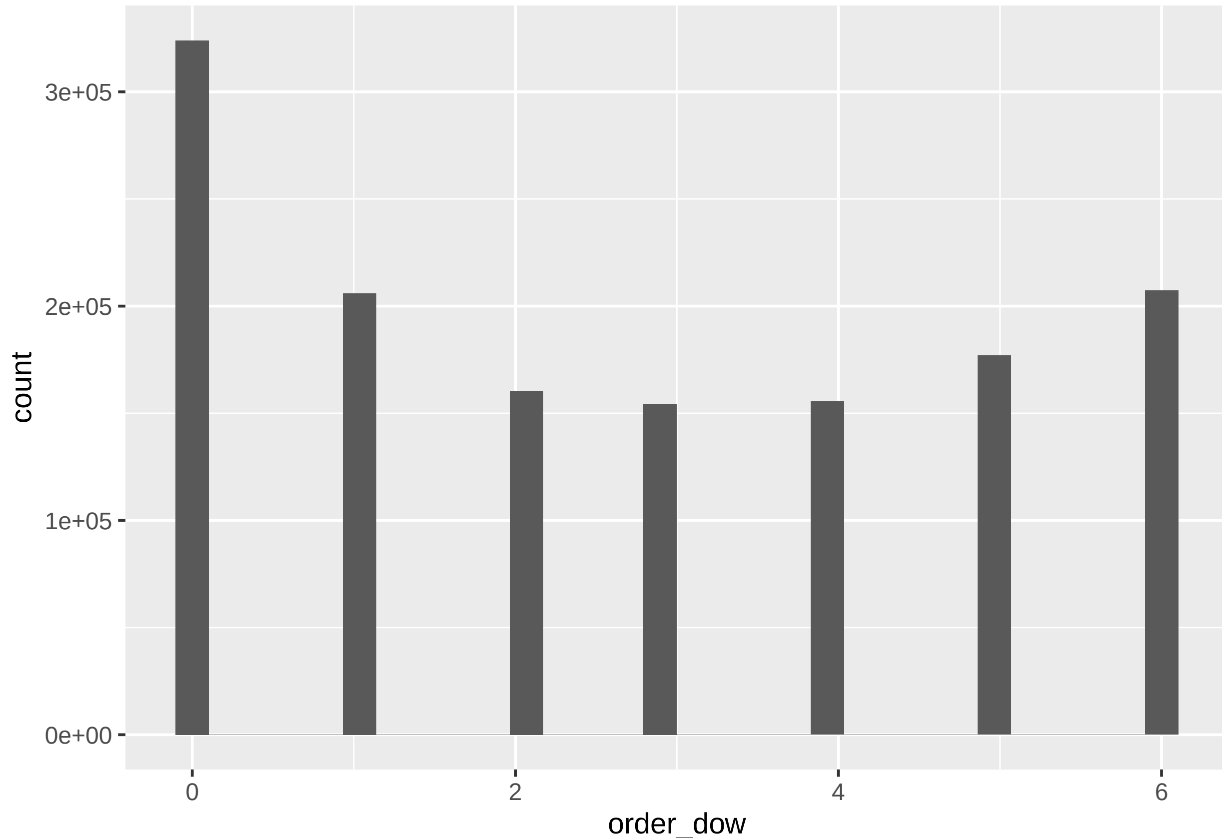



Most orders come from the produce aisle, with snacks and dairy, eggs among the top 3 department aisles.

'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`.
```

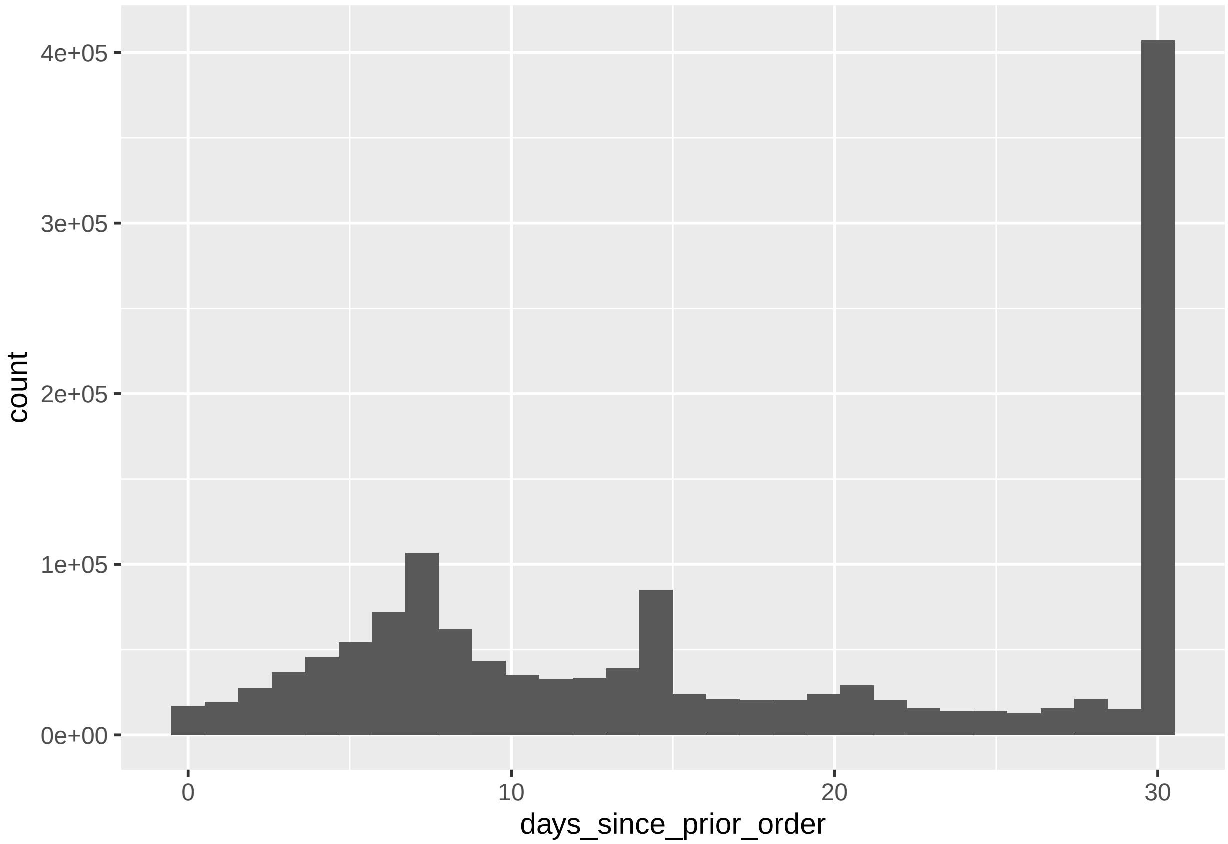



It is assumed for order_dow that 0=Sunday, 1=Monday, 2=Wednesday… and so on until 6=Saturday. Sunday, Monday and Saturday appear to be the most common days where people place their orders.

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.

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

kable(percentage, caption = "Percentage of Transactions for Top 10 Products, from Instacart Training Ord
```

Table 1: Percentage of Transactions for Top 10 Products, from Instacart Training Orders data

| product_name | count | pct |
|---|---|---|
| Banana | 18726 | 1.3524318 |
| Bag of Organic Bananas | 15480 | 1.1179987 |
| Organic Strawberries | 10894 | 0.7867880 |
| Organic Baby Spinach | 9784 | 0.7066214 |

| product_name | count | pct |
|---|---|---|
| Large Lemon | 8135 | 0.5875271 |
| Organic Avocado | 7409 | 0.5350938 |
| Organic Hass Avocado | 7293 | 0.5267161 |
| Strawberries | 6494 | 0.4690106 |
| Limes | 6033 | 0.4357162 |
| Organic Raspberries | 5546 | 0.4005440 |

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))
```

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 takes reordered dataframe as input and outputs it as a markdown table
kable(reordered, caption = "Reorederd products from the Instacart orders training data set showing the p
```

Table 2: Reorederd products from the Instacart orders training data set showing the proportion of reordered transactions that contain the product

| 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 |

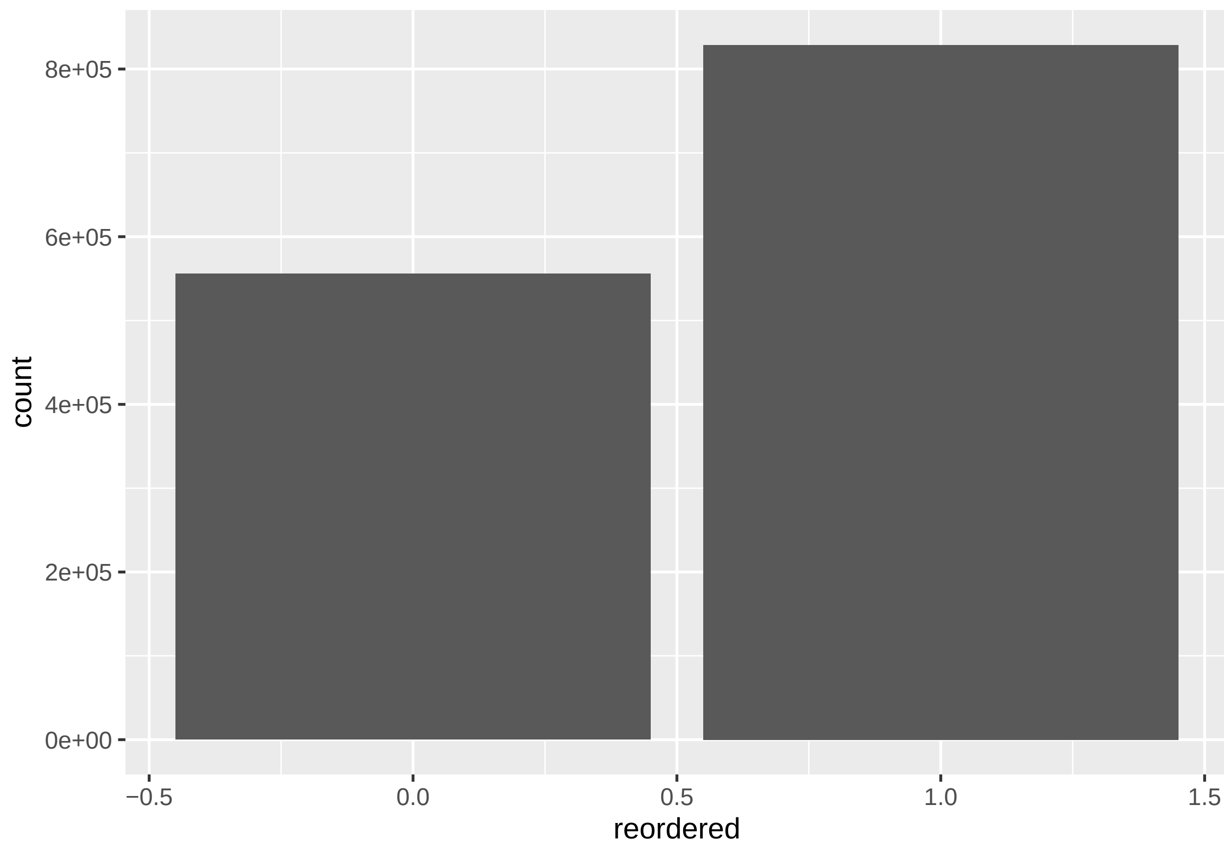



Figure 3: Bar chart of transactions from the Instacart training dataset showing whether the product ordered is the first time a user ordered that product (0) or the product is an item that the user is reordering (1).

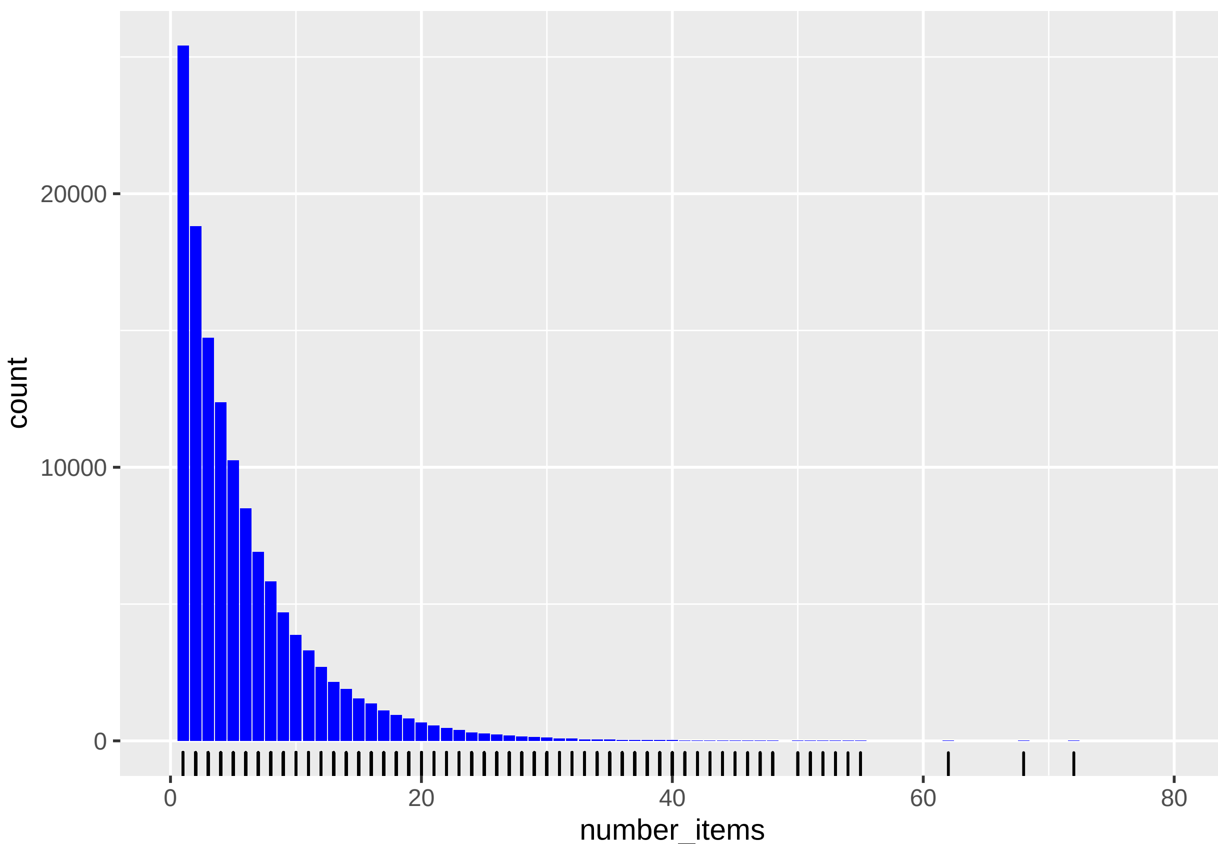



Figure 4: Histogram of number of items in each transaction for the Instacart training orders dataset. The histogram shows a skewed distribution to the right, where most of the transactions contain 0 - 5 items.

## Data Cleansing

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)
library(dplyr)

#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
```

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

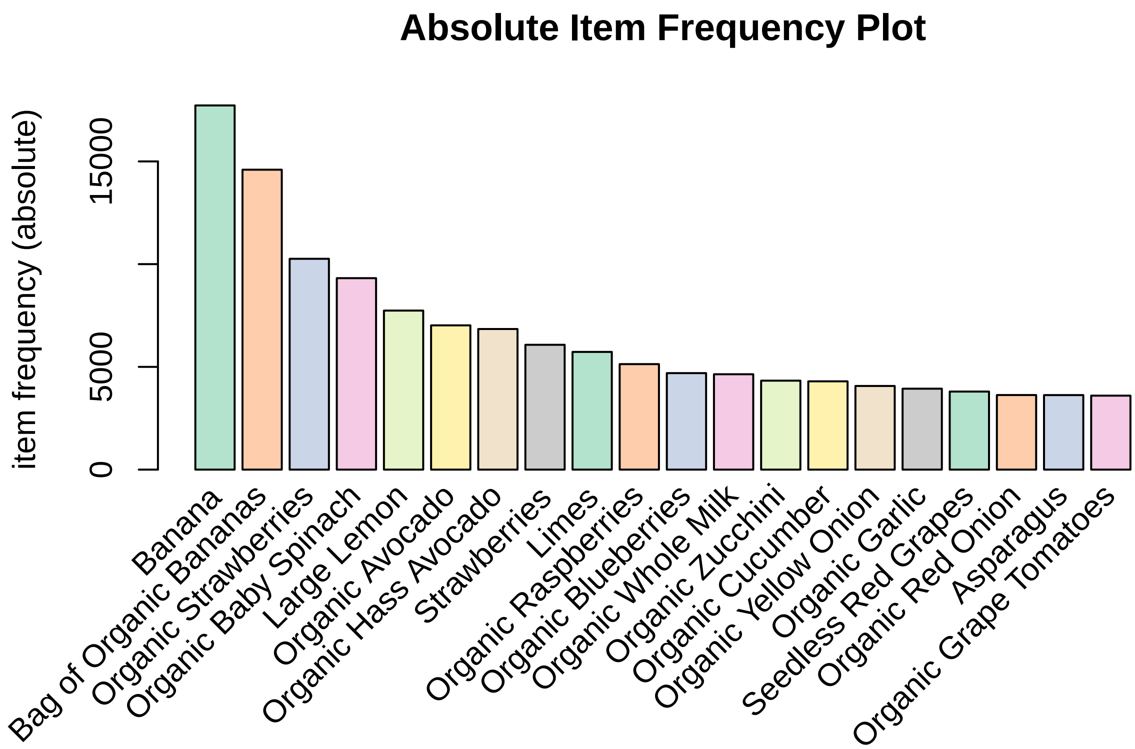
A sparse matrix is a matrix in which most elements are zero.

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
```

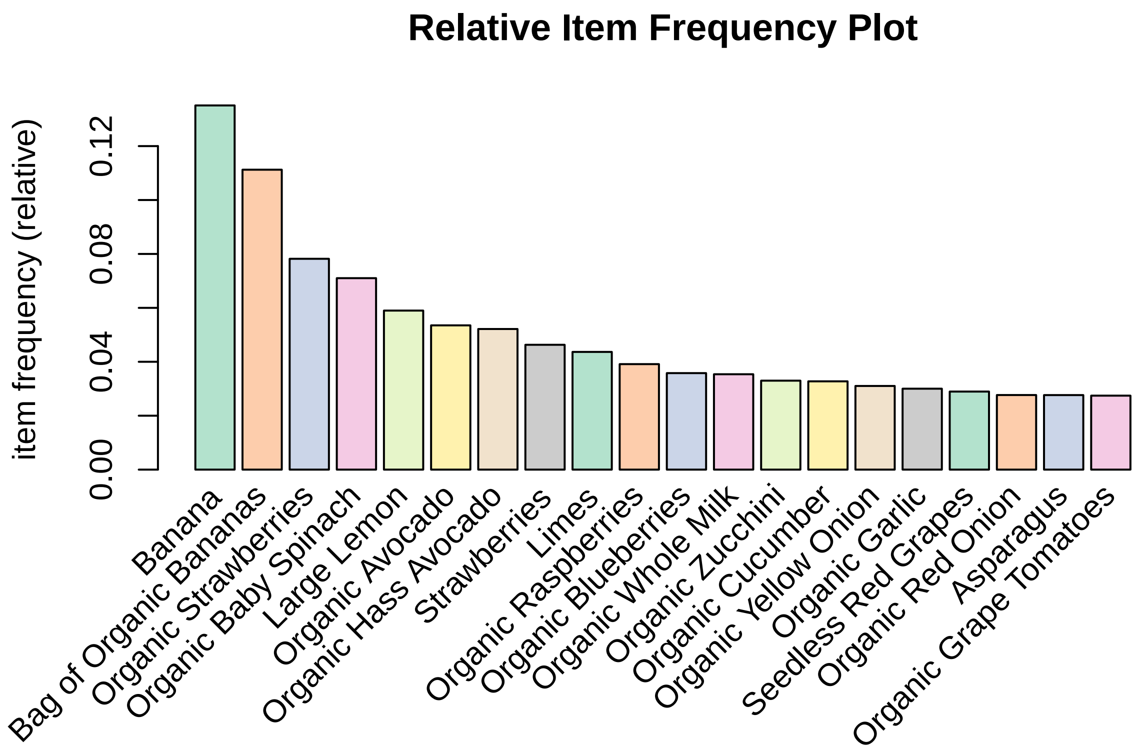



According to the frequency plot, the top 20 products bought in Instacart are banana, bag of organic bananas, organic strawberries, organic baby spinach, large lemon, organic avocado, organic hass avocado, strawberries, limes, organic raspberries, organic blueberries, organic whole milk, organic zucchini,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

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 [0.85s].
## sorting and recoding items ... [1812 item(s)] done [0.02s].
## creating transaction tree ... done [0.10s].
## checking subsets of size 1 2 3 4 done [0.10s].
## writing ... [255 rule(s)] done [0.00s].
## creating S4 object  ... done [0.07s].
```

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 [0.68s].
## 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 [0.02s].
```

```
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
```

From the results we can see that customers that buy Mini & Mobile usually also buy Natural Artesian Water, while people who buy Americano often also buy proscuitto.

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 [0.84s].
## 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 ... [3 rule(s)] done [0.01s].
## creating S4 object  ... done [0.02s].
```

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:

```r
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 [0.85s].
## sorting and recoding items ... [1812 item(s)] done [0.02s].
## 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:

```r
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

```r
#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 method=visualization method to be used(scatterplot, 2 key plot, matrix3D)

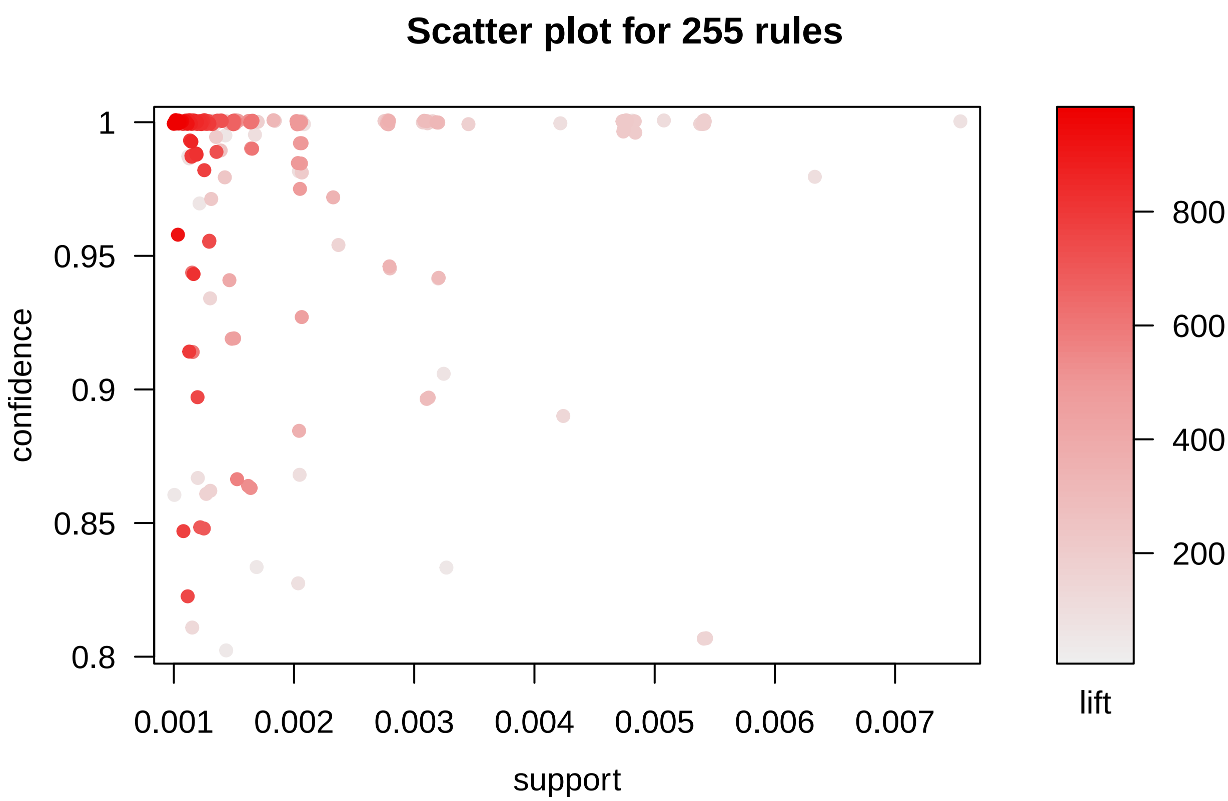



Figure 5: Scatterplot for association rules filtered for confidence over 60%, produced using Apriori algorithm, with Instacart Orders training data

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

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

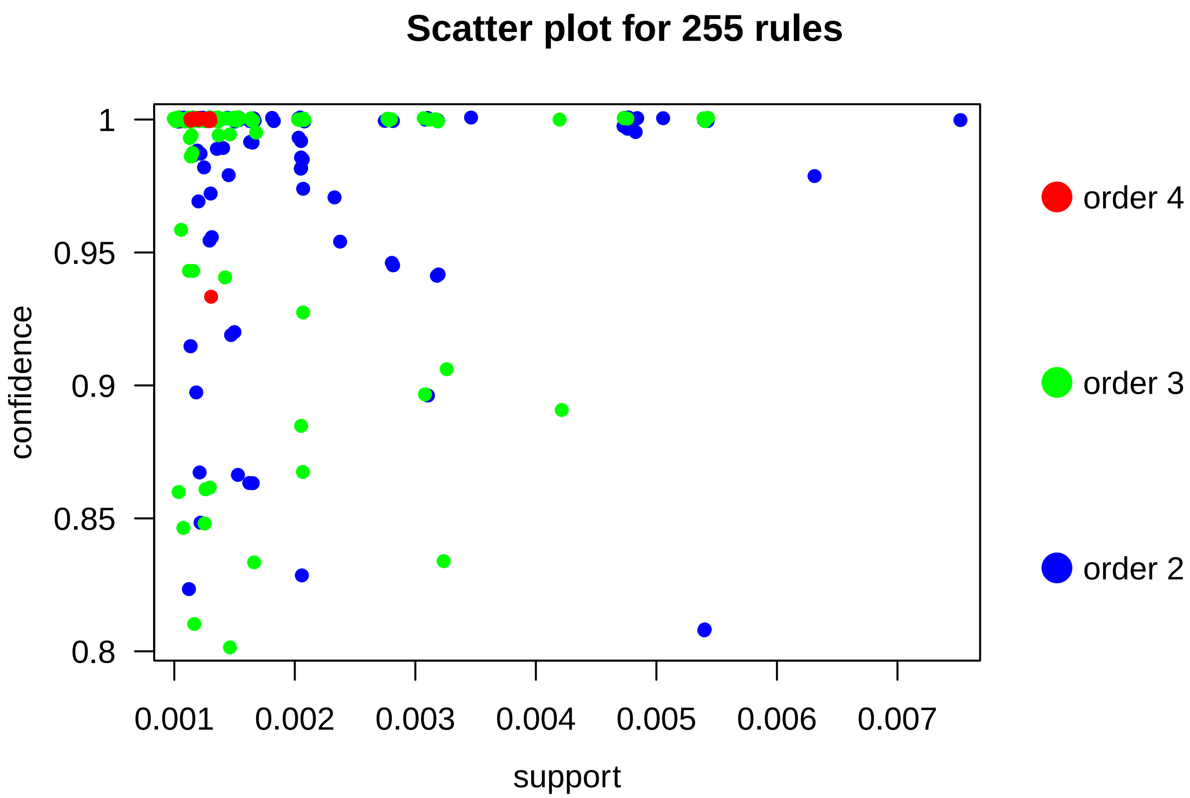



Figure 6: 2 key plot for association rules filtered for confidence greater than 60% using Apriori algorithm, from Instacart training orders dataset

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).

```r
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:

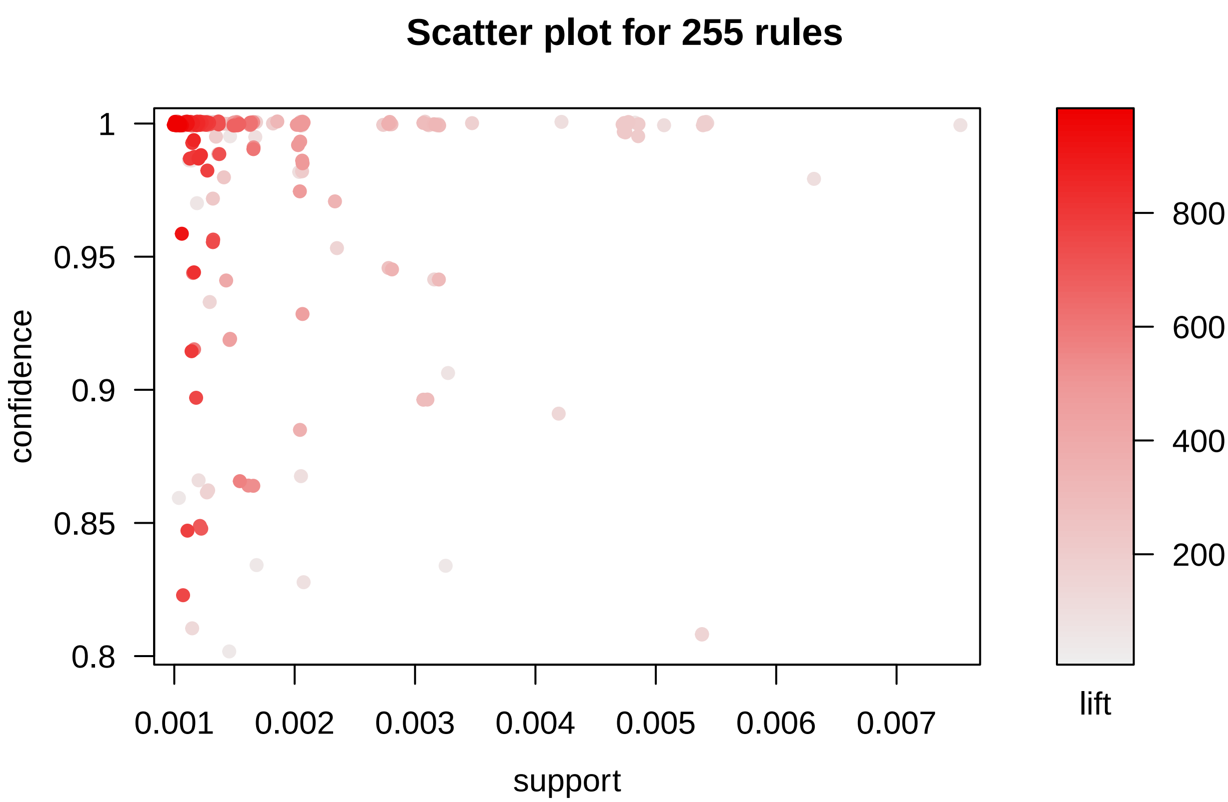
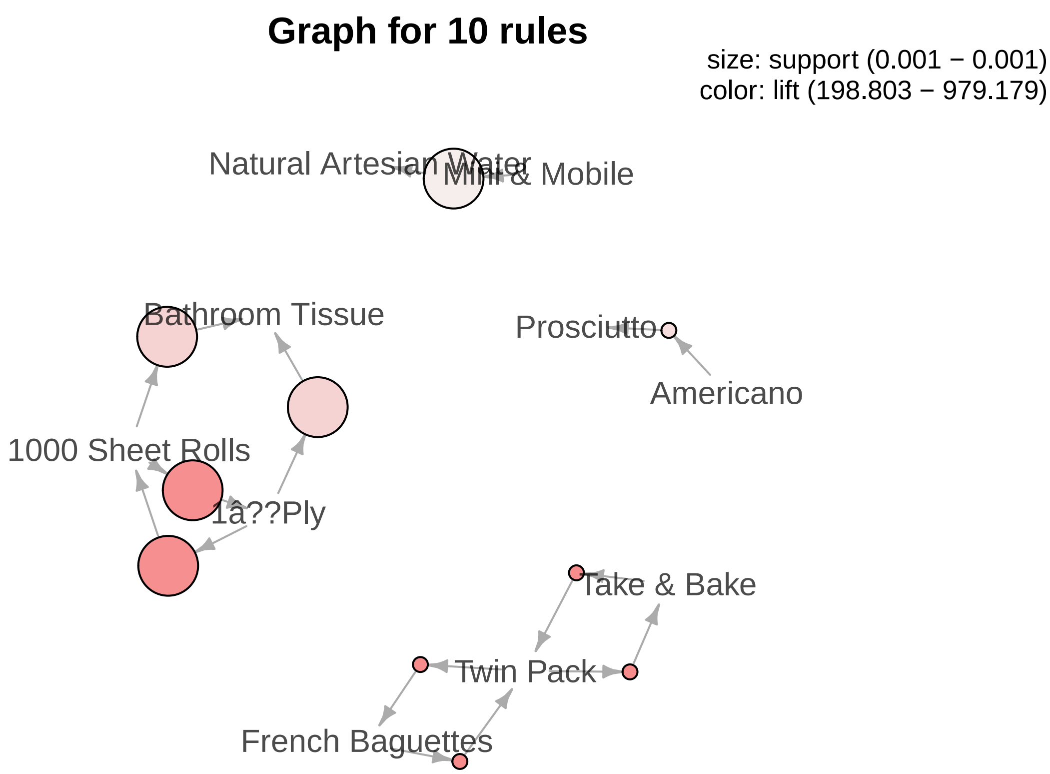



Figure 7: scatterplot for association rules using apriori algorithm, from Instacart orders training dataset.

```
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")
```

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

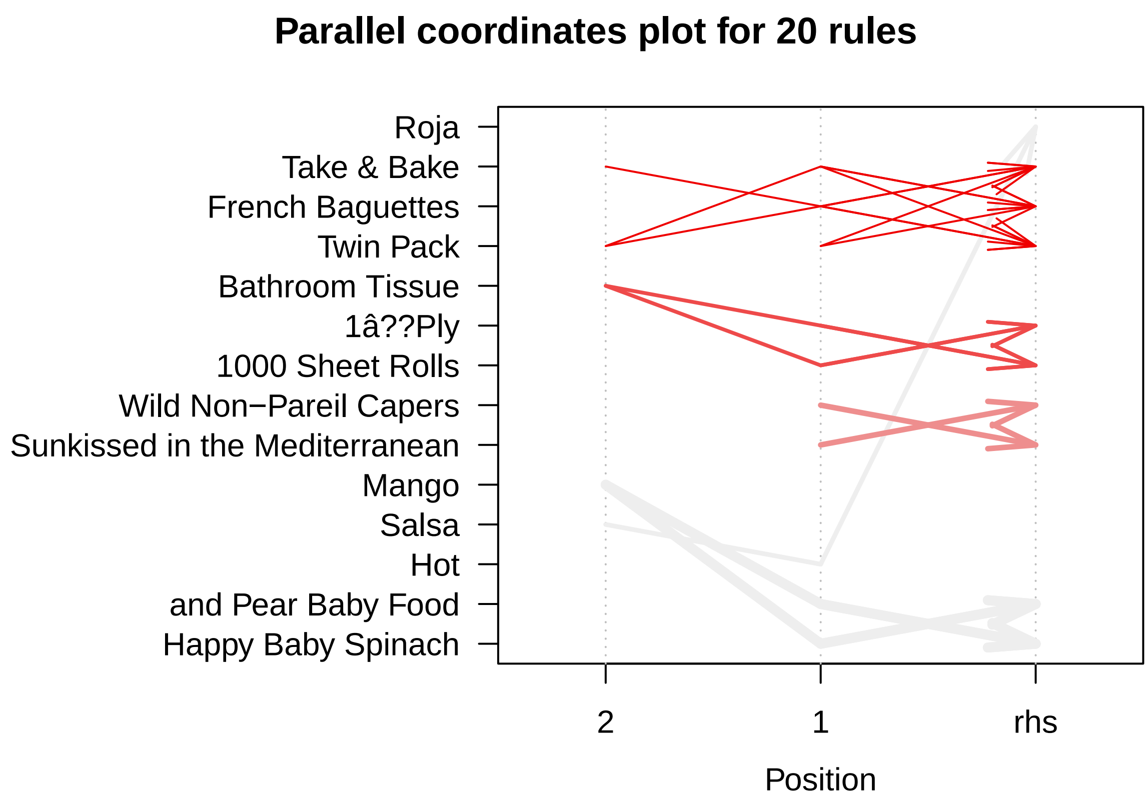



Figure 8: Parallel coordinates plot for 20 association rules. RHS is the item suggested for customers, based on the items already in the cart at 1, and 2.

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

## Data Cleaning

#### Item based collaborative filtering for Implicit Data

The concept of making recommendations from Implicit data is inspired by work outlined in http://yifanhu.net/PUB/cf.pdf by Hu, Korenand and Volinsky.R portion of the project is inspired from https://github.com/willsmorgan/Recommender-Systems-using-W-ALS/blob/master/W-ALS%20Final.pdf by William Morgan. Here we are trying to find similar products from transaction history and make recommendations for our users.We have implicit data that how many times user has purchased a instacart product.We are only using products, users and order quantity from the instacart dataset. We can assume that an product purchased with many times by a user implies positive feedback. In this method we focus on what we know the user has purchased and the confidence we have in whether or not they like any given item. We had around three million user interactions from reordered products. Here we are considering only 8K users and 16K products who have reordered items from online cart.

```
#Extract columns for matrix
#transactions<-X[,c("user_id","product_id","order_id")]            #if using training orders data
transactions<-prior_order[,c("user_id","product_id","order_id")]    #using prior orders data


#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
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.
```

```
dim(interactions)
```

```
## [1] 244355      3
```

## Matrix Factorisation

In Matrix Factorization we take the original matrix and factor into user and product latent factors.Matrix factorization mathematically reduce the dimensionality of our original "all users by all items" matrix into something much smaller that represents "all items by some taste dimensions" and "all users by some taste dimensions.Doing this reduction and working with fewer dimensions makes it both much more computationally efficient and but also gives us better results. The user transactions data which can be turned into a list where each row indicates whether or not a user bought a product (1 = bought, 0 = not bought). With implicit data the difference lies in how we deal with all the not bought one's in our very sparse matrix.We can't assume value for missing information and We don't know if a missing value means the user dislike the product, or they never interacted with data. Basically we need some way to learn from the missing data.

First we need to convert our dataframe to sparse matrix.Here we are creating rowid's and column id's for user and product for Sparse matrix.

#### 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"
```

Sparse matrices are special data structures that allows for efficient storage of sparse data (such as large matrices with few non-zero elements). Sparse matrices are able to store the same data as a dense matrix using much less memory.

One way to store data in sparse format is by keeping just the co-ordinates of non-zero elements (cmdline, 2019). Three vectors of the same size are used: i, j, and x. Vectors i, and j specify the coordinates of the non-zero elements, where i is the row index and j is the column index. The vector x stores the actual non-zero values.

Combine the ids for sparse matrix with dataframe and create the sparse matrix

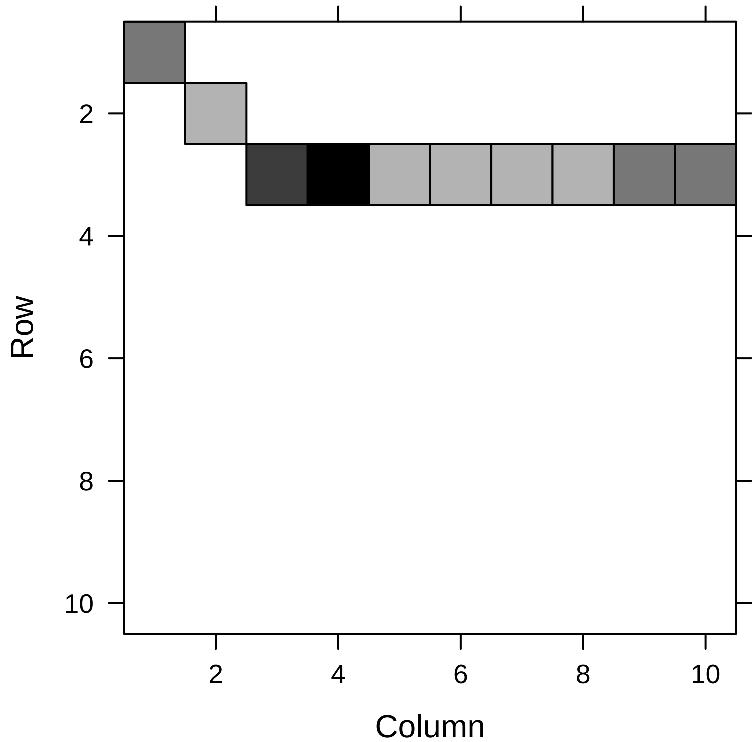
```
#sparse matrix
data<-interactions_sample %>%
  inner_join(user_enc, by = 'user_id') %>%
  inner_join(product_enc, by = 'product_id')



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

To visualize a small portion of the sparse matrix using the image function in R:

```
image(X[1:10, 1:10])
```




**Dimensions: 10 x 10**

The majority of the graph should be white, indicating sparse with no data.

Split dataset into test and train:

```
#test set

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

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

```
# 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)
```

```
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)
```

Determine confidence function using the linear method suggested by WALS algorithms authors

```
#  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)
}
```

Value of alpha is determined by cross-validation:

```
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)
```

```
# 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  [00:29:22.250] starting factorization with 8 threads
## INFO  [00:29:22.925] iter 1 loss = 0.6594
## INFO  [00:29:23.611] iter 2 loss = 0.3642
## INFO  [00:29:24.317] iter 3 loss = 0.3298
## INFO  [00:29:25.020] iter 4 loss = 0.3159
## INFO  [00:29:25.711] iter 5 loss = 0.3074
## INFO  [00:29:26.416] iter 6 loss = 0.3015
## INFO  [00:29:27.112] iter 7 loss = 0.2969
## INFO  [00:29:27.792] iter 8 loss = 0.2933
## INFO  [00:29:28.520] iter 9 loss = 0.2903
## INFO  [00:29:29.367] iter 10 loss = 0.2878
```

```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)
```

```r
#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 we can compare common algorithms typically used to create recommendery systems. In Recommenderlab, 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.

```r
# 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
```

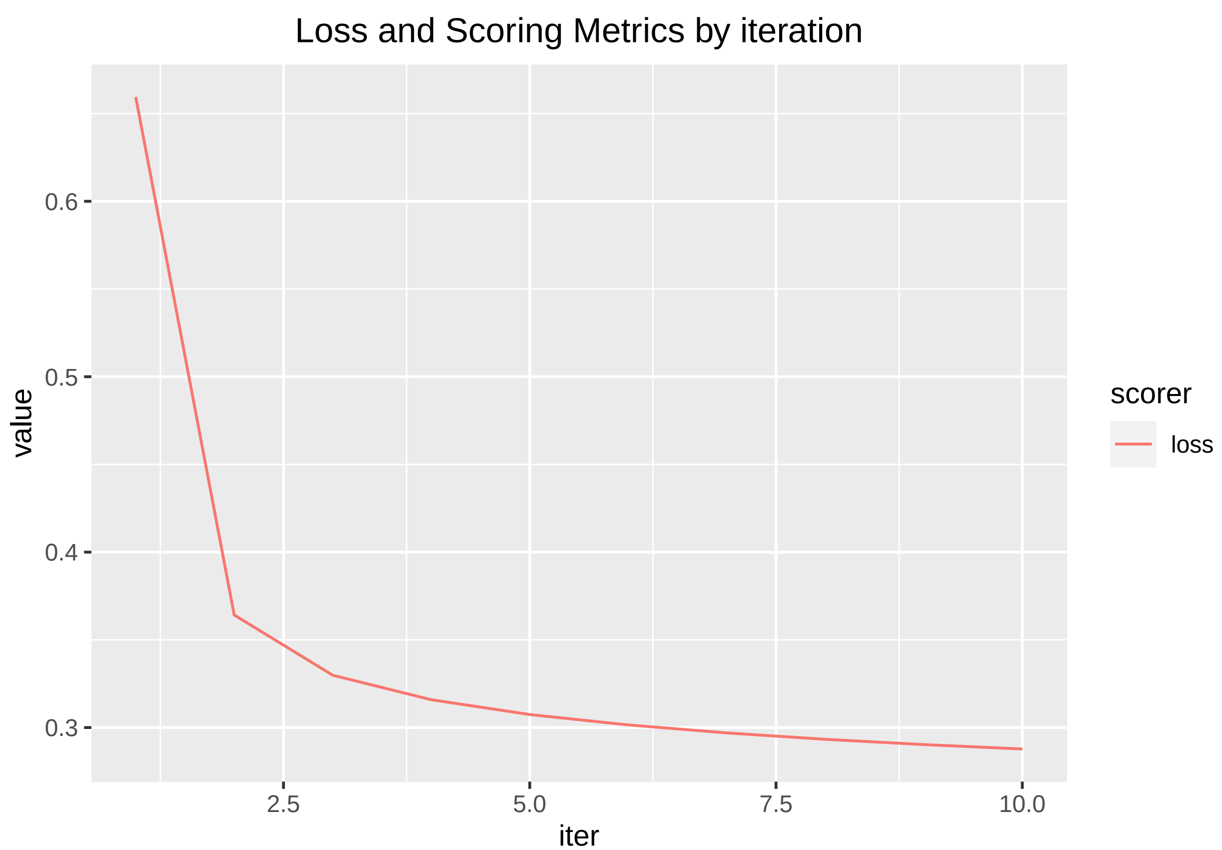



Figure 9: Plot of Loss and Scoring metrics by Iteration

```
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

  )
```

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: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   4090896  218.5   11325796  604.9  11325796  604.9
## Vcells 358236470 2733.2  719387754 5488.5 719158681 5486.8
```

```
#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  [0.1sec/182.79sec]
##   2  [0.14sec/180.43sec]
##   3  [0.07sec/194.96sec]
##   4  [0.08sec/176.15sec]
##   5  [0.07sec/172.43sec]
## RANDOM run fold/sample [model time/prediction time]
##   1  [0sec/1.64sec]
##   2  [0sec/1.63sec]
##   3  [0sec/1.83sec]
##   4  [0sec/1.73sec]
##   5  [0sec/1.76sec]
## POPULAR run fold/sample [model time/prediction time]
##   1  [0sec/10.71sec]
##   2  [0sec/10.79sec]
##   3  [0.01sec/11.02sec]
##   4  [0.01sec/11.24sec]
##   5  [0.01sec/10.75sec]
## IBCF run fold/sample [model time/prediction time]
##   1  [0.23sec/1.33sec]
##   2  [0.28sec/1.2sec]
##   3  [0.2sec/1.28sec]
##   4  [0.23sec/1.5sec]
##   5  [0.24sec/1.33sec]
```

```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"]]
```

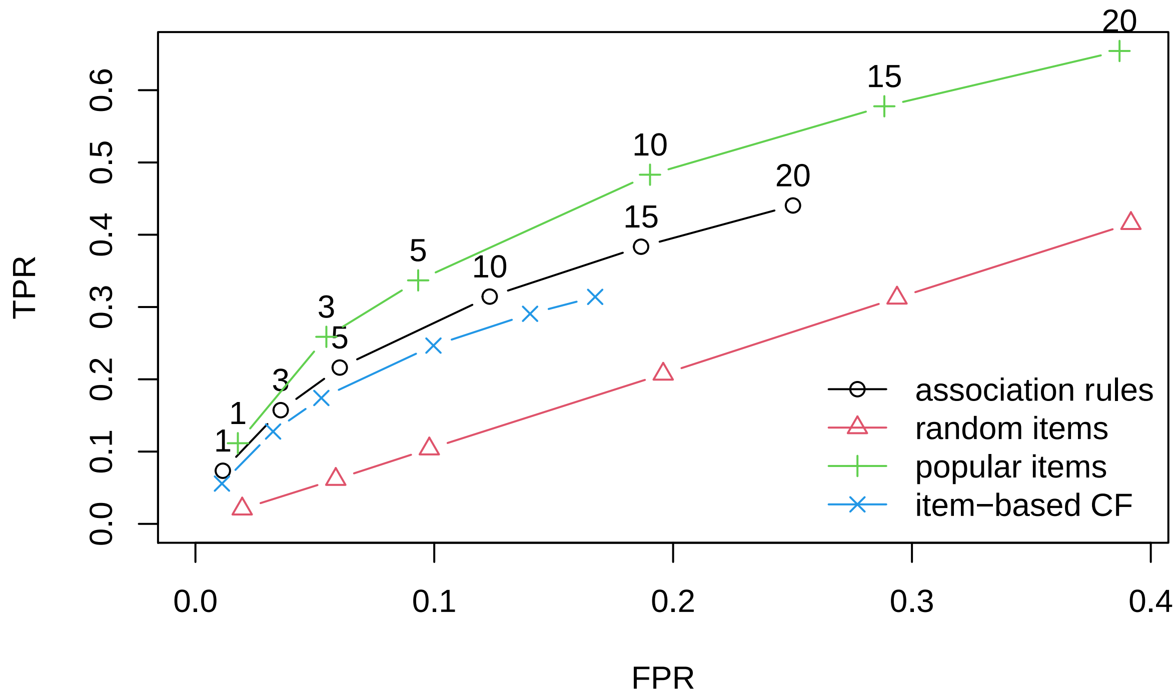
```
## Evaluation results for 5 folds/samples using method 'IBCF'.
```

### Visualise the Results

Use plot function from recommenderlab to compare model performance

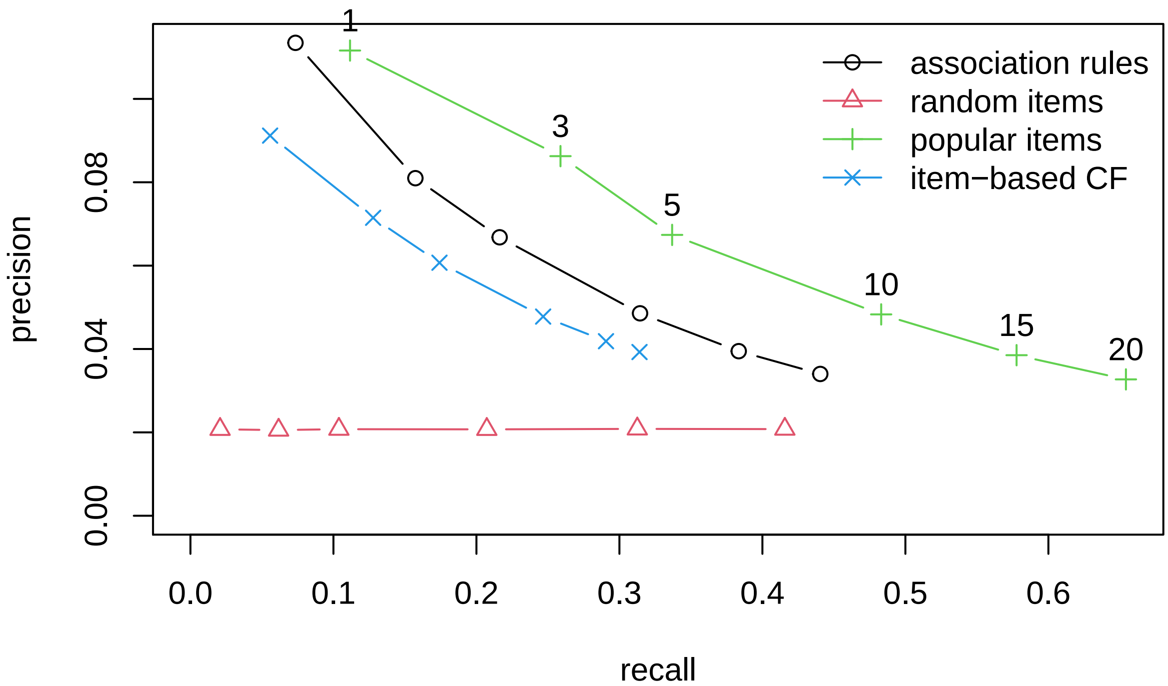
Arrange confusion matrix for one model in a convenient format:

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




Comparison of ROC curves. For this dataset 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 algorithms 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.

## Deployment

Instacart can use our recommendation models to recommend products to customers while they do their shopping, through a "Frequently bought with x (item)" suggestions. Additionally, our other model using Weighted Alternating Least Squares with Implicit Feedback model can also make suggestions for grocery products, based on the implicit feedback given when customers previously bought a product to suggest products for future purchases.

Other data that can be collected include product price, and transaction date. In other recommendation systems, user ratings of products can also be used to recommend new products, using different algorithms such as user-based collaborative filtering. The current model is based on customer transactions buying groceries from Instacart in 2017, and thus recommendations are based on those transactions. The model could be updated every 2 years or so with new transaction data because in that time, new products may be added, new food trends would also mean customers may make different product choices based on new food trends in the future. For example, plant-based products, breakfast foods, pasta, pickling and fermenting kits, meal kits are predicted to become very popular in 2021 (Hearst Magazine, 2021), and customer purchases may reflect those trends (which may be different from what they typically bought in 2017).

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