Final project Step 2

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In this step, I've started to import libraries and data. I'll be looking at the data with str() function and also will be seeing the first few rows by head() function. Later on, I'll be creating the matrices of genres of movies so that the recommenderlab could work with the data.

Importing libraries

Importing the dataset

```
setwd("~/MSDS/DSC520/dsc520/Final_project")
movie_data <- read.csv("IMDB-Dataset/movies.csv", stringsAsFactors=FALSE)
rating_data <- read.csv("IMDB-Dataset/ratings.csv")
str(movie_data)
```

```
## 'data.frame':    10329 obs. of  3 variables:
##  $ movieId: int  1 2 3 4 5 6 7 8 9 10 ...
##  $ title  : chr  "Toy Story (1995)" "Jumanji (1995)" "Grumpier Old Men (1995)" "Waiting to Exhale (19
##  $ genres : chr  "Adventure|Animation|Children|Comedy|Fantasy" "Adventure|Children|Fantasy" "Comedy|R
```

Glimpse of the data

```
# Movies data
head(movie_data)
```

```
##   movieId                               title
## 1       1                    Toy Story (1995)
## 2       2                      Jumanji (1995)
## 3       3             Grumpier Old Men (1995)
## 4       4            Waiting to Exhale (1995)
## 5       5 Father of the Bride Part II (1995)
## 6       6                           Heat (1995)
##                                         genres
## 1 Adventure|Animation|Children|Comedy|Fantasy
## 2                  Adventure|Children|Fantasy
## 3                               Comedy|Romance
```

```
## 4                         Comedy|Drama|Romance
## 5                                       Comedy
## 6                       Action|Crime|Thriller
```

```
# Ratings data
head(rating_data)
```

```
##   userId movieId rating  timestamp
## 1      1      16    4.0 1217897793
## 2      1      24    1.5 1217895807
## 3      1      32    4.0 1217896246
## 4      1      47    4.0 1217896556
## 5      1      50    4.0 1217896523
## 6      1     110    4.0 1217896150
```

```
# extracting the genres as a dataframe
movie_genre <- as.data.frame(movie_data$genres, stringsAsFactors=FALSE)

# Splitting the collective genres into individual ones
movie_genre2 <- as.data.frame(tstrsplit(movie_genre[,1], '[|]', type.convert=TRUE), stringsAsFactors=FA

# Assigning column names as serial numbers assuming each movie may have maximum of 10 genres
colnames(movie_genre2) <- c(1:10)
```

```
# List of all the genres

list_genre <- unique(movie_genre2[c("1")])[1:18,] # there was 19 values but last one was without genre

#list_genre <- c("Action", "Adventure", "Animation", "Children", "Comedy",
    #            "Crime","Documentary","Drama", "Fantasy", "Film-Noir",
      #          "Horror","Musical", "Mystery","Romance","Sci-Fi", "Thriller", "War", "Western")

# Initializing a matrix
genre_mat1 <- matrix(0,10330,18)

genre_mat1[1,] <- list_genre

# Assigning genres  as column names
colnames(genre_mat1) <- list_genre

for (index in 1:nrow(movie_genre2)) {
  for (col in 1:ncol(movie_genre2)) {
    gen_col = which(genre_mat1[1,] == movie_genre2[index,col])
    genre_mat1[index+1,gen_col] <- 1 }}


genre_mat2 <- as.data.frame(genre_mat1[-1,], stringsAsFactors=FALSE) #removing first row, which was the

for (col in 1:ncol(genre_mat2)) {
  genre_mat2[,col] <- as.integer(genre_mat2[,col]) #convert from characters to integers
  }

str(genre_mat2)
```

```
## 'data.frame':    10329 obs. of  18 variables:
##  $ Adventure  : int  1 1 0 0 0 0 0 1 0 1 ...
##  $ Comedy     : int  1 0 1 1 1 0 1 0 0 0 ...
##  $ Action     : int  0 0 0 0 0 1 0 0 1 1 ...
##  $ Drama      : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ Crime      : int  0 0 0 0 0 1 0 0 0 0 ...
##  $ Children   : int  1 1 0 0 0 0 0 1 0 0 ...
##  $ Mystery    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Animation  : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ Documentary: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Thriller   : int  0 0 0 0 0 1 0 0 0 1 ...
##  $ Horror     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Fantasy    : int  1 1 0 0 0 0 0 0 0 0 ...
##  $ Western    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Film-Noir  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Romance    : int  0 0 1 1 0 0 1 0 0 0 ...
##  $ Sci-Fi     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Musical    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ War        : int  0 0 0 0 0 0 0 0 0 0 ...
```

Combining the genre matrix with the movies data resulting in a search matrix

```
SearchMatrix <- cbind(movie_data[,1:2], genre_mat2[])
head(SearchMatrix)
```

```
##   movieId                              title Adventure Comedy Action Drama
## 1       1                  Toy Story (1995)         1      1      0     0
## 2       2                    Jumanji (1995)         1      0      0     0
## 3       3           Grumpier Old Men (1995)         0      1      0     0
## 4       4          Waiting to Exhale (1995)         0      1      0     1
## 5       5 Father of the Bride Part II (1995)         0      1      0     0
## 6       6                       Heat (1995)         0      0      1     0
##   Crime Children Mystery Animation Documentary Thriller Horror Fantasy Western
## 1     0        1       0         1           0        0      0       1       0
## 2     0        1       0         0           0        0      0       1       0
## 3     0        0       0         0           0        0      0       0       0
## 4     0        0       0         0           0        0      0       0       0
## 5     0        0       0         0           0        0      0       0       0
## 6     1        0       0         0           0        1      0       0       0
##   Film-Noir Romance Sci-Fi Musical War
## 1         0       0      0       0   0
## 2         0       0      0       0   0
## 3         0       1      0       0   0
## 4         0       1      0       0   0
## 5         0       0      0       0   0
## 6         0       0      0       0   0
```

For the movie recommendation system to make sense of the ratings through recommenderlabs, we have to convert our matrix into a sparse matrix one. This new matrix is of the class 'realRatingMatrix'.

```
ratingMatrix <- reshape2::dcast(rating_data, userId~movieId, value.var = "rating", na.rm=FALSE)
ratingMatrix <- as.matrix(ratingMatrix[,-1]) #remove userIds

#Convert rating matrix into a recommenderlab sparse matrix
ratingMatrix <- as(ratingMatrix, "realRatingMatrix")
ratingMatrix
```

```
## 668 x 10325 rating matrix of class 'realRatingMatrix' with 105339 ratings.
```

Exploring recommendation model options

```
recommendation_model <- recommenderRegistry$get_entries(dataType = "realRatingMatrix")
names(recommendation_model)
```

```
##  [1] "HYBRID_realRatingMatrix"       "ALS_realRatingMatrix"
##  [3] "ALS_implicit_realRatingMatrix" "IBCF_realRatingMatrix"
##  [5] "LIBMF_realRatingMatrix"        "POPULAR_realRatingMatrix"
##  [7] "RANDOM_realRatingMatrix"       "RERECOMMEND_realRatingMatrix"
##  [9] "SVD_realRatingMatrix"          "SVDF_realRatingMatrix"
## [11] "UBCF_realRatingMatrix"
```

Since we're interested to create the model based on IBCF algorithm or Item Based Collaborative filtering, let's look at the parameters for that.

```
recommendation_model$IBCF_realRatingMatrix$parameters
```

```
## $k
## [1] 30
##
## $method
## [1] "Cosine"
##
## $normalize
## [1] "center"
##
## $normalize_sim_matrix
## [1] FALSE
##
## $alpha
## [1] 0.5
##
## $na_as_zero
## [1] FALSE
```

#Exploring similar data Collaborative Filtering involves suggesting movies to the users that are based on collecting preferences from many other users. For example, if a user A likes to watch action films and so does user B, then the movies that the user B will watch in the future will be recommended to A and vice-versa. Therefore, recommending movies is dependent on creating a relationship of similarity between the two users. With the help of recommenderlab, we can compute similarities using various operators like cosine, pearson as well as jaccard.

```
similarity_mat <- similarity(ratingMatrix[1:4, ],
                             method = "cosine",
                             which = "users")
as.matrix(similarity_mat)
```

```
##           1         2         3         4
## 1 0.0000000 0.9760860 0.9641723 0.9914398
## 2 0.9760860 0.0000000 0.9925732 0.9374253
## 3 0.9641723 0.9925732 0.0000000 0.9888968
## 4 0.9914398 0.9374253 0.9888968 0.0000000
```

```
#image(as.matrix(similarity_mat), main = "User's similarities")
```

In the above matrix, each row and column represents a user. I have taken four users and each cell in this matrix represents the similarity that is shared between the two users. Now, I delineate the similarity that is shared between the films.

```
movie_similarity <- similarity(ratingMatrix[, 1:4], method =
                                 "cosine", which = "items")
as.matrix(movie_similarity)
```

```
##           1         2         3         4
## 1 0.0000000 0.9669732 0.9559341 0.9101276
## 2 0.9669732 0.0000000 0.9658757 0.9412416
## 3 0.9559341 0.9658757 0.0000000 0.9864877
## 4 0.9101276 0.9412416 0.9864877 0.0000000
```

```
#image(as.matrix(movie_similarity), main = "Movies similarity")
```

I'm now going to extract the most unique ratings:

```
rating_values <- as.vector(ratingMatrix@data)
# extracting unique ratings
unique(rating_values)
```

```
##  [1] 0.0 5.0 4.0 3.0 4.5 1.5 2.0 3.5 1.0 2.5 0.5
```

Now, I will create a table of ratings that will display the most unique ratings.

```
Table_of_Ratings <- table(rating_values) # creating a count of movie ratings
Table_of_Ratings
```

```
## rating_values
##       0     0.5       1     1.5       2     2.5       3     3.5       4     4.5
## 6791761    1198    3258    1567    7943    5484   21729   12237   28880    8187
##       5
##   14856
```

Most Viewed Movies Visualization

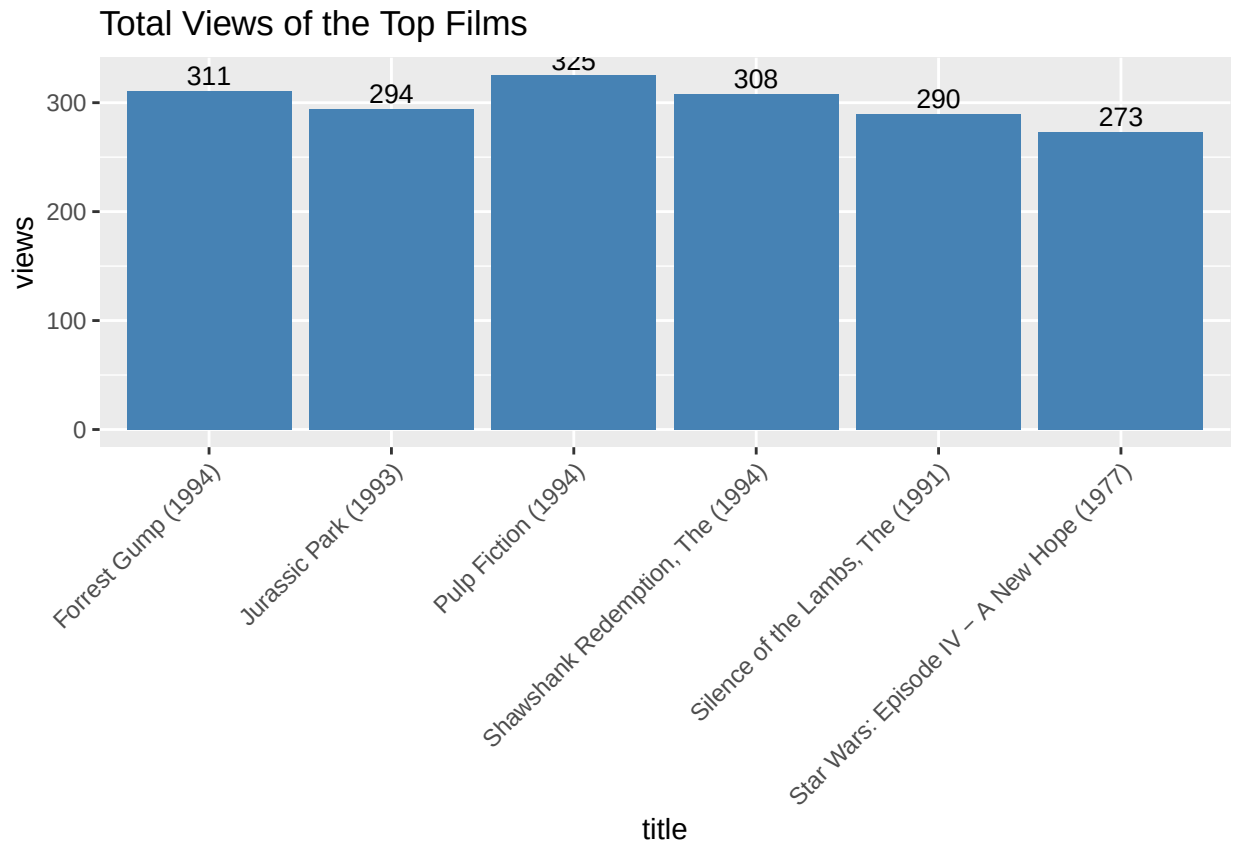
In this section of the machine learning project, we will explore the most viewed movies in our dataset. We will first count the number of views in a film and then organize them in a table that would group them in descending order.

```
library(ggplot2)
# count views for each movie
movie_views <- colCounts(ratingMatrix)
table_views <- data.frame(movie = names(movie_views),
                          views = movie_views) # create dataframe of views
# sort by number of views
table_views <- table_views[order(table_views$views,
                                 decreasing = TRUE), ]
table_views$title <- NA
for (index in 1:10325){
  table_views[index,3] <- as.character(subset(movie_data,
                                          movie_data$movieId == table_views[index,1])$title)
}
table_views[1:6,]
```

```
##     movie views                                        title
## 296   296   325                      Pulp Fiction (1994)
## 356   356   311                      Forrest Gump (1994)
## 318   318   308          Shawshank Redemption, The (1994)
## 480   480   294                     Jurassic Park (1993)
## 593   593   290          Silence of the Lambs, The (1991)
## 260   260   273 Star Wars: Episode IV - A New Hope (1977)
```

Now, let's visualize a bar plot for the total number of views of the top films using ggplot2 package.

```
ggplot(table_views[1:6, ], aes(x = title, y = views)) +
  geom_bar(stat="identity", fill = 'steelblue') +
  geom_text(aes(label=views), vjust=-0.3, size=3.5) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  ggtitle("Total Views of the Top Films")
```

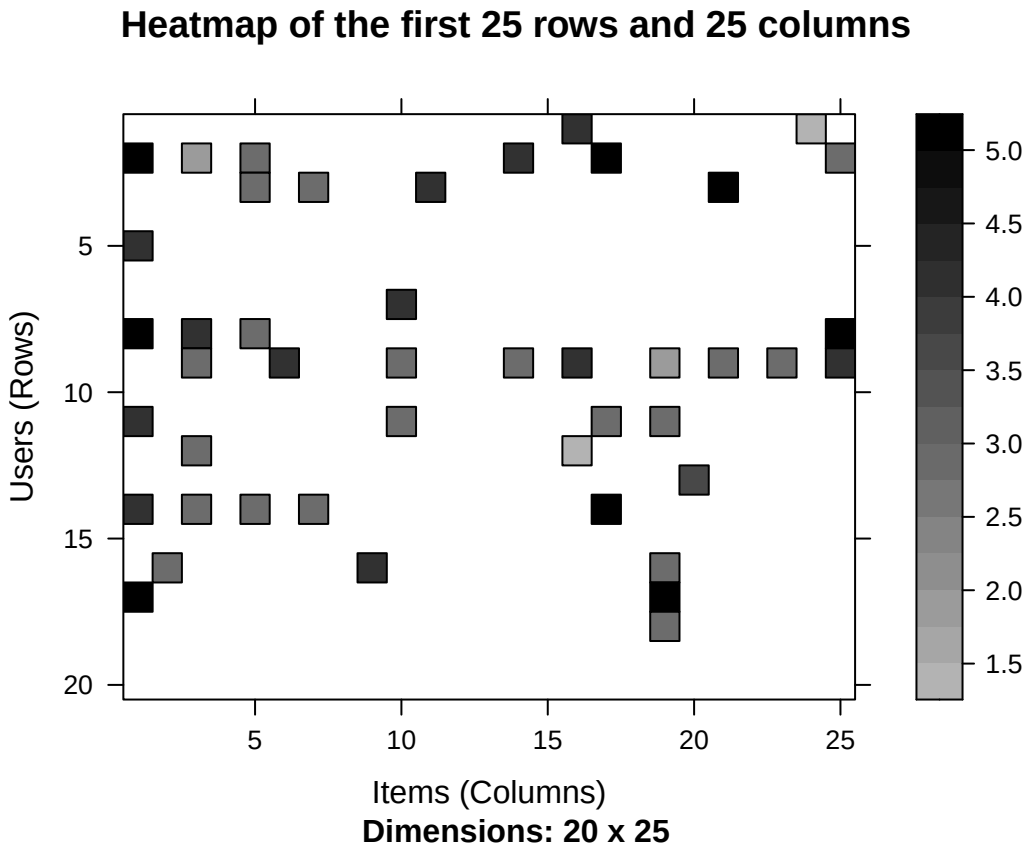


From the chart above, it is clearly evident that most-watched movie is Pulp Fiction (1994) followed by Forrest Gump(1994).

Heatmap of Movie ratings

Now I'm going to visualize a heatmap of the movie ratings. It will contain24 rows and 25 columns.

```
image(ratingMatrix[1:20, 1:25], axes = FALSE, main = "Heatmap of the first 25 rows and 25 columns")
```



Data preparation

Selecting useful data

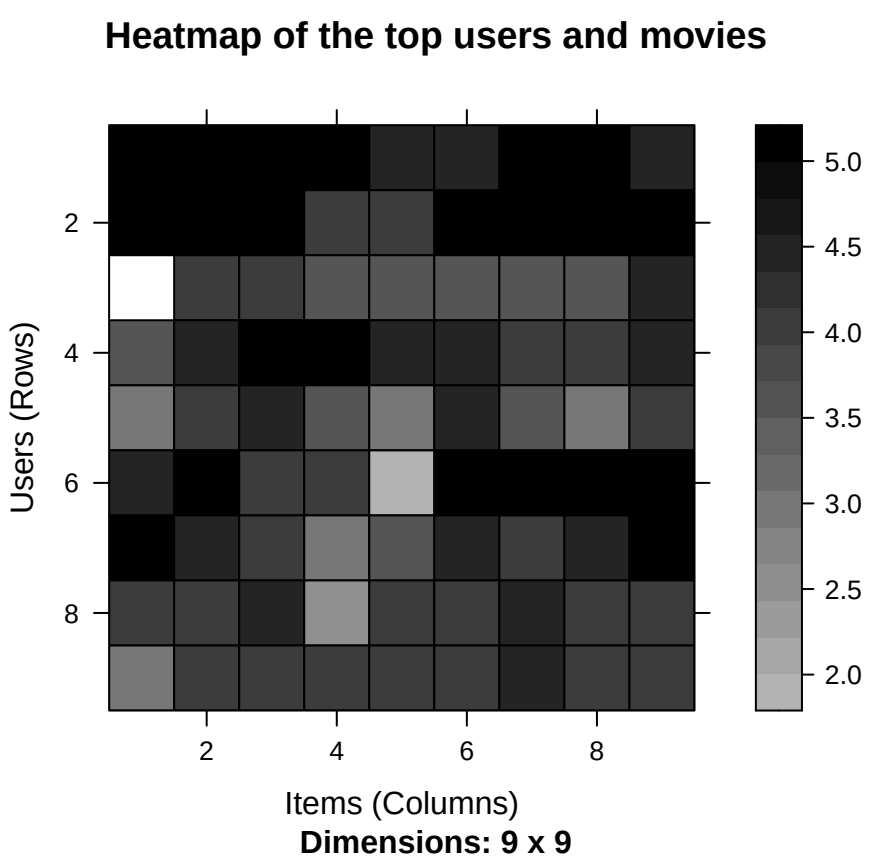
For finding useful data in our dataset, the set threshold for the minimum number of users who have rated a film is 50. This is also same for minimum number of views that are per film. This way, We'll have filtered a list of watched films from least-watched ones.

```
movie_ratings <- ratingMatrix[rowCounts(ratingMatrix) > 50,
                              colCounts(ratingMatrix) > 50]
movie_ratings
```

```
## 420 x 447 rating matrix of class 'realRatingMatrix' with 38341 ratings.
```

From the above output of 'movie_ratings', we observe that there are 420 users and 447 films as opposed to the previous 668 users and 10325 films. We can now delineate our matrix of relevant users as follows –

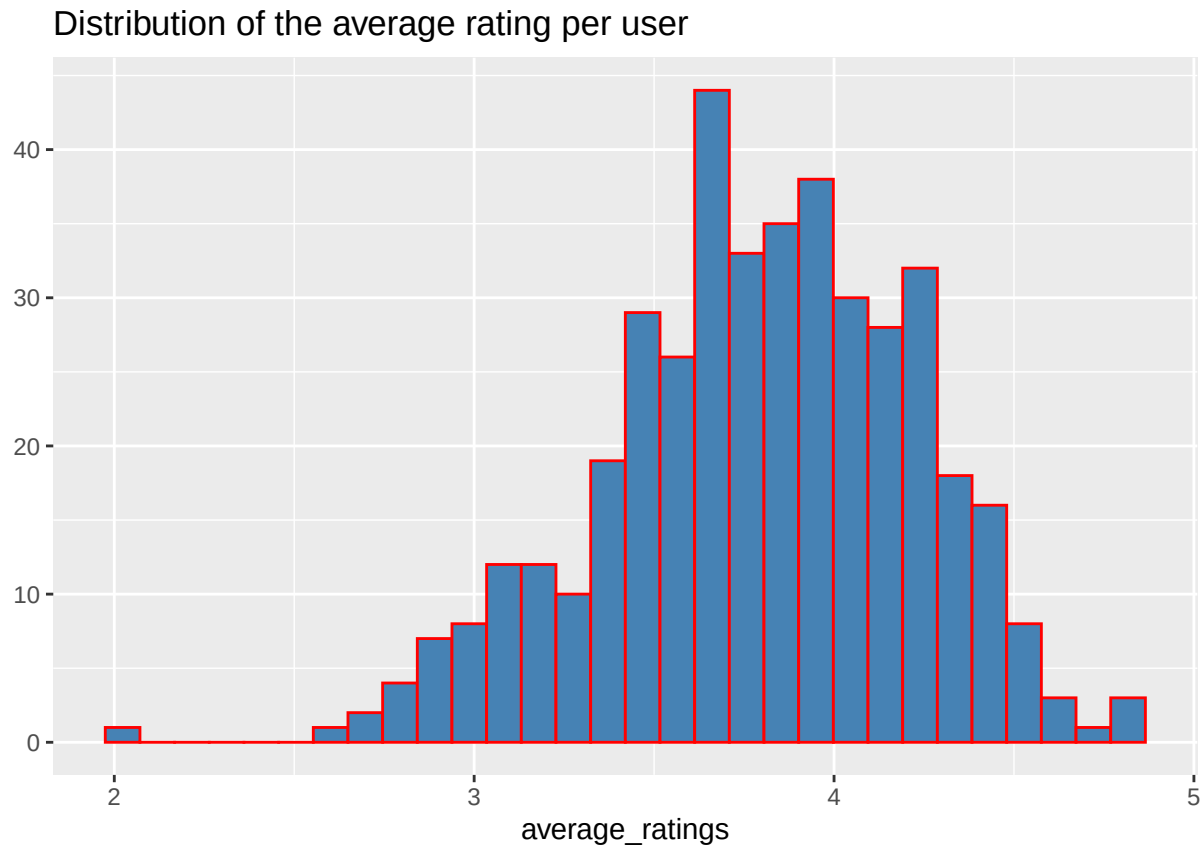
```
minimum_movies<- quantile(rowCounts(movie_ratings), 0.98)
minimum_users <- quantile(colCounts(movie_ratings), 0.98)
image(movie_ratings[rowCounts(movie_ratings) > minimum_movies,
                    colCounts(movie_ratings) > minimum_users],
main = "Heatmap of the top users and movies")
```



Now, we will visualize the distribution of the average ratings per user.

```
average_ratings <- rowMeans(movie_ratings)
qplot(average_ratings, fill=I("steelblue"), col=I("red")) +
  ggtitle("Distribution of the average rating per user")
```

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



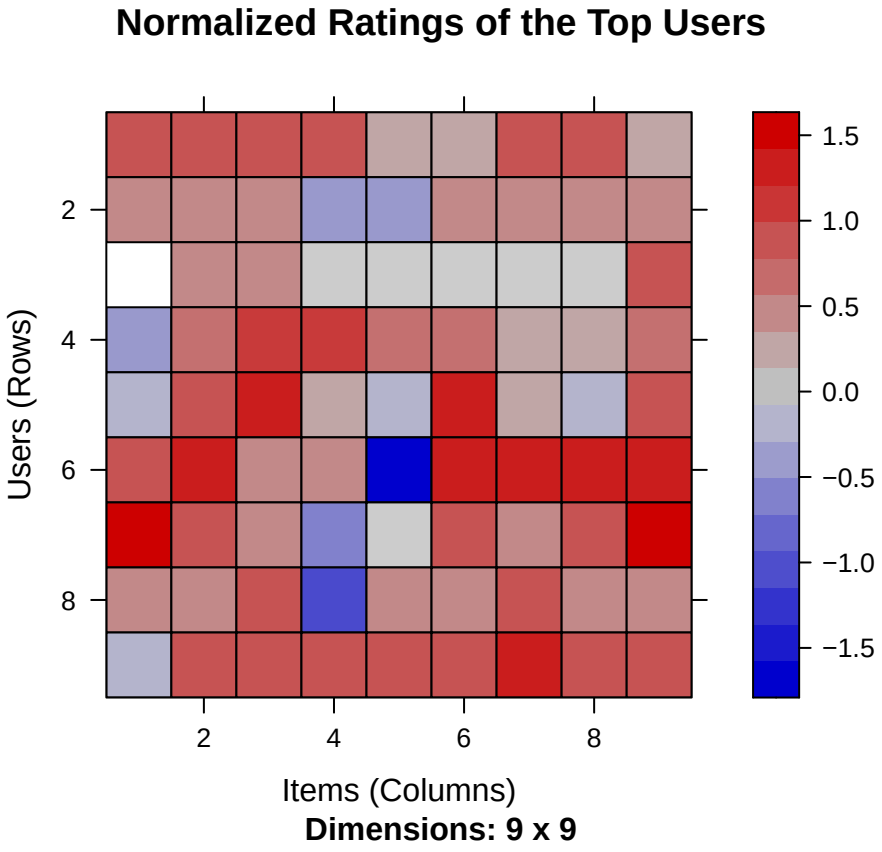
Data Normalization

In the case of some users, there can be high ratings or low ratings provided to all of the watched films. This will act as a bias while implementing the model. In order to remove this, we neeed to normalize the data. Normalization is a data preparation procedure to standardize the numerical values in a column to a common scale value. This is done in such a way that there is no distortion in the range of values. Normalization transforms the average value of our ratings column to 0. We then plot a heatmap that delineates our normalized ratings.

```
normalized_ratings <- normalize(movie_ratings)
sum(rowMeans(normalized_ratings) > 0.00001)
```

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

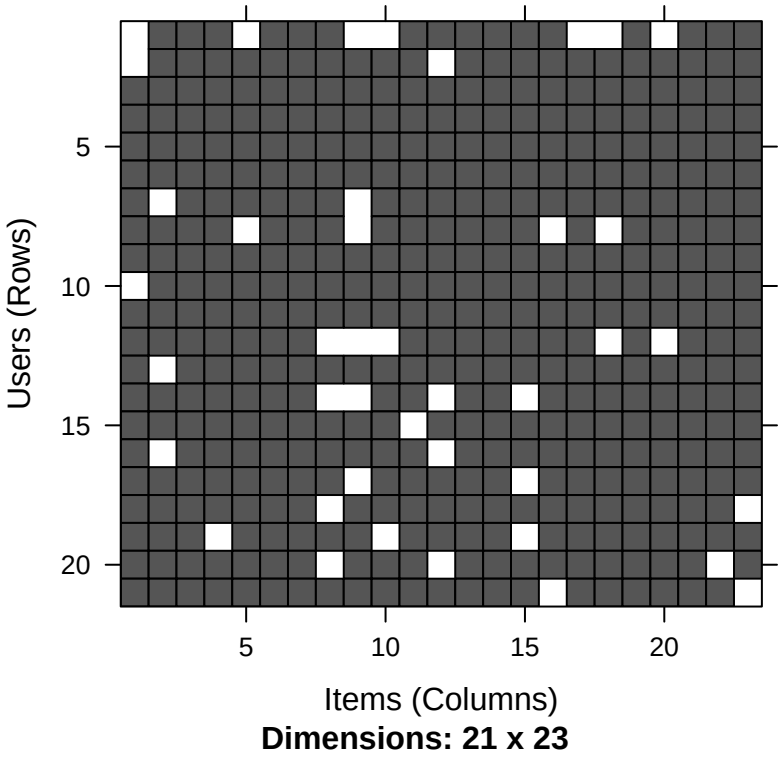
```
image(normalized_ratings[rowCounts(normalized_ratings) > minimum_movies,
                         colCounts(normalized_ratings) > minimum_users],
main = "Normalized Ratings of the Top Users")
```



Data binarization

In this final step of data preparation, I'm going to binarize the data. Binarizing the data means that we have two discrete values 1 and 0, which will allow our recommendation systems to work more efficiently. We will define a matrix that will consist of 1 if the rating is above 3 and otherwise it will be 0.

```
binary_minimum_movies <- quantile(rowCounts(movie_ratings), 0.95)
binary_minimum_users <- quantile(colCounts(movie_ratings), 0.95)
#movies_watched <- binarize(movie_ratings, minRating = 1)
good_rated_films <- binarize(movie_ratings, minRating = 3)
image(good_rated_films[rowCounts(movie_ratings) > binary_minimum_movies,
colCounts(movie_ratings) > binary_minimum_users],
main = "Heatmap of the top users and movies")
```



Collaborative Filtering System

Now, we will develop our very own Item Based Collaborative Filtering System. This type of collaborative filtering finds similarity in the items based on the people's ratings of them. The algorithm first builds a similar-items table of the customers who have purchased them into a combination of similar items. This is then fed into the recommendation system.

The similarity between single products and related products can be determined with the following algorithm –

- For each Item i1 present in the product catalog, purchased by customer C.
- And, for each item i2 also purchased by the customer C.
- Create record that the customer purchased items i1 and i2.
- Calculate the similarity between i1 and i2. We will build this filtering system by splitting the dataset into 80% training set and 20% test set.

```
sampled_data<- sample(x = c(TRUE, FALSE),
                      size = nrow(movie_ratings),
                      replace = TRUE,
                      prob = c(0.8, 0.2))
training_data <- movie_ratings[sampled_data, ]
testing_data <- movie_ratings[!sampled_data, ]
```

Building the Recommendation System

We will now explore the various parameters of our Item Based Collaborative Filter. These parameters are default in nature. In the first step, k denotes the number of items for computing their similarities. Here, k is equal to 30. Therefore, the algorithm will now identify the k most similar items and store their number.

```
recommendation_system <- recommenderRegistry$get_entries(dataType ="realRatingMatrix")
recommendation_system$IBCF_realRatingMatrix$parameters
```

```
## $k
## [1] 30
##
## $method
## [1] "Cosine"
##
## $normalize
## [1] "center"
##
## $normalize_sim_matrix
## [1] FALSE
##
## $alpha
## [1] 0.5
##
## $na_as_zero
## [1] FALSE
```

```
## Recommender of type 'IBCF' for 'realRatingMatrix'
## learned using 341 users.
```

```
## [1] "Recommender"
## attr(,"package")
## [1] "recommenderlab"
```

Using the getModel() function, we will retrieve the recommen_model. We will then find the class and dimensions of our similarity matrix that is contained within model_info. Finally, we will generate a heatmap, that will contain the top 20 items and visualize the similarity shared between them.

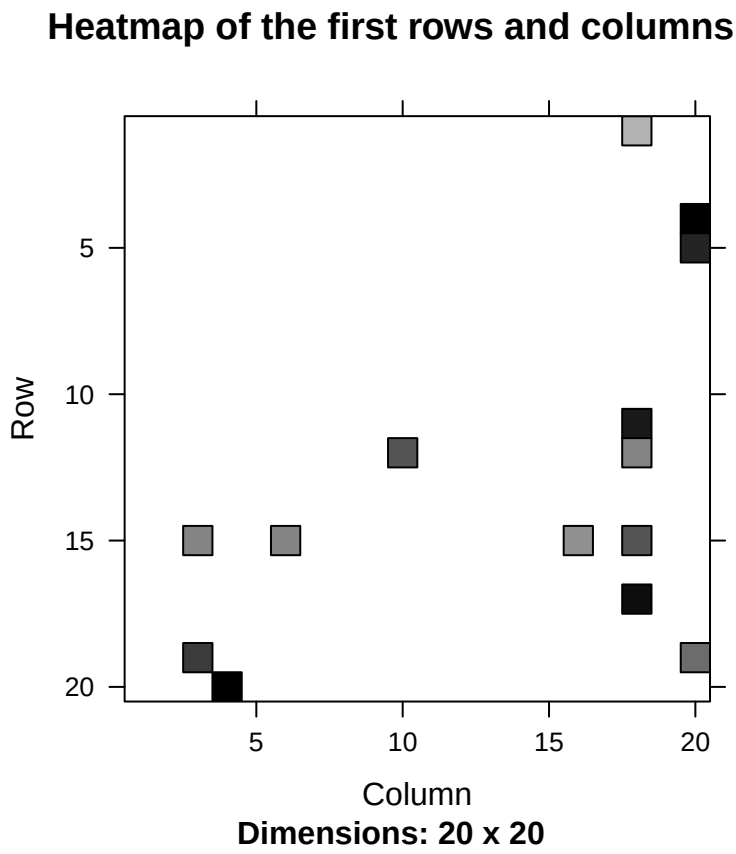
```
model_info <- getModel(recommen_model)
class(model_info$sim)
```

```
## [1] "dgCMatrix"
## attr(,"package")
## [1] "Matrix"
```

```
dim(model_info$sim)
```

```
## [1] 447 447
```

```
top_items <- 20
image(model_info$sim[1:top_items, 1:top_items],
   main = "Heatmap of the first rows and columns")
```



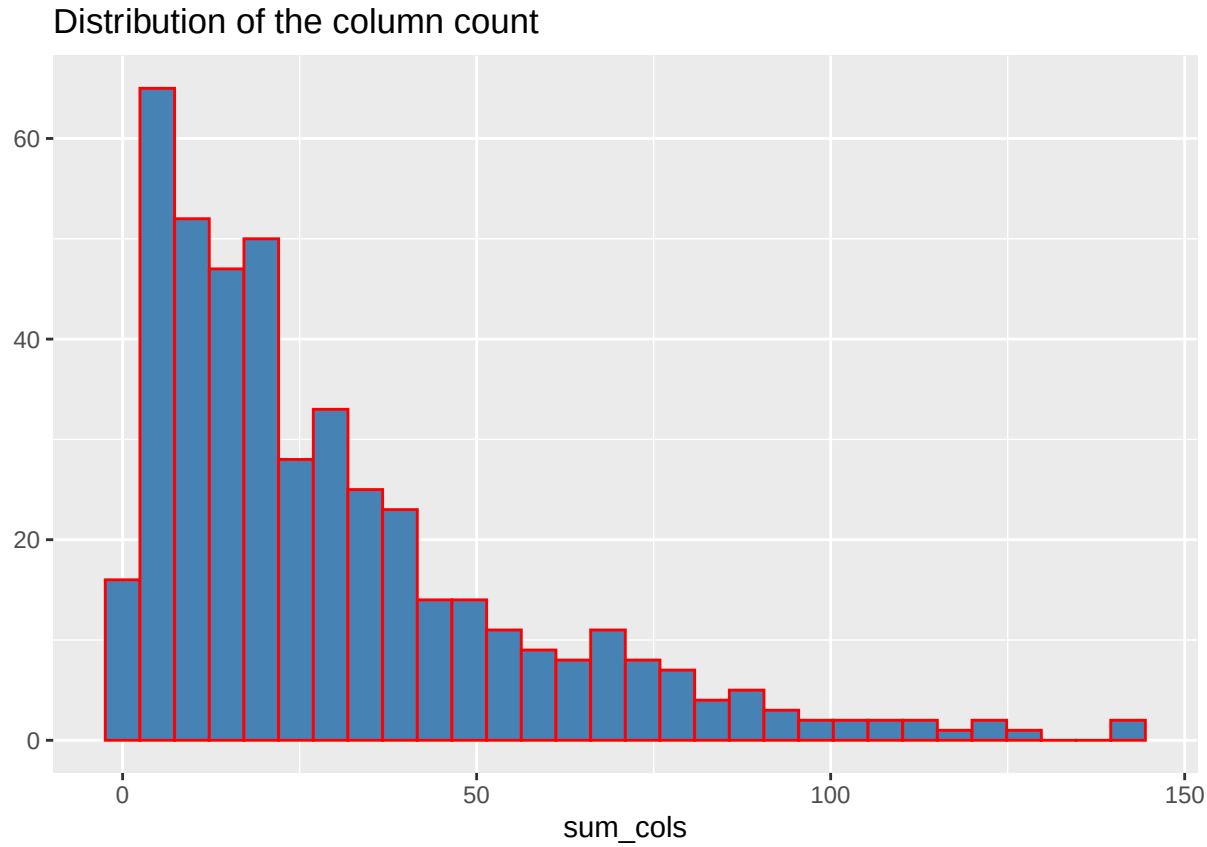
Next step, we will carry out the sum of rows and columns with the similarity of the objects above 0. We will visualize the sum of columns through a distribution as follows –

```
sum_rows <- rowSums(model_info$sim > 0)
table(sum_rows)
```

```
## sum_rows
##  30
## 447
```

```
sum_cols <- colSums(model_info$sim > 0)
qplot(sum_cols, fill=I("steelblue"), col=I("red"))+ ggtitle("Distribution of the column count")
```

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



We will create a top_recommendations variable which will be initialized to 10, specifying the number of films to each user. We will then use the predict() function that will identify similar items and will rank them appropriately. Here, each rating is used as a weight. Each weight is multiplied with related similarities. Finally, everything is added in the end.

```
# the number of items to recommend to each user
top_recommendations <- 10
predicted_recommendations <- predict(object = recommen_model,
                          newdata = testing_data,
                          n = top_recommendations)
predicted_recommendations
```

```
## Recommendations as 'topNList' with n = 10 for 79 users.
```

```
user1 <- predicted_recommendations@items[[1]] # recommendation for the first user
movies_user1 <- predicted_recommendations@itemLabels[user1]
movies_user2 <- movies_user1
for (index in 1:10){
  movies_user2[index] <- as.character(subset(movie_data,
                                        movie_data$movieId == movies_user1[index])$title)
}
movies_user2
```

```
##  [1] "First Knight (1995)"
##  [2] "Johnny Mnemonic (1995)"
```

```
##  [3] "Judge Dredd (1995)"
##  [4] "Species (1995)"
##  [5] "Waterworld (1995)"
##  [6] "Interview with the Vampire: The Vampire Chronicles (1994)"
##  [7] "Like Water for Chocolate (Como agua para chocolate) (1992)"
##  [8] "Legends of the Fall (1994)"
##  [9] "Santa Clause, The (1994)"
## [10] "Dragonheart (1996)"
```

```r
# matrix with the recommendations for each user
recommendation_matrix <- sapply(predicted_recommendations@items,
                      function(x){ as.integer(colnames(movie_ratings)[x]) })
recommendation_matrix[,1:4]
```

```
##       [,1] [,2] [,3] [,4]
##  [1,]  168  529 4963   25
##  [2,]  172 2023 2321  231
##  [3,]  173  736 1088  364
##  [4,]  196  509 3751  368
##  [5,]  208  724 5418  919
##  [6,]  253  508 2599 1917
##  [7,]  265  920  349 2005
##  [8,]  266  266  553 2028
##  [9,]  317  104 3175 3418
## [10,]  653  261  596 4720
```