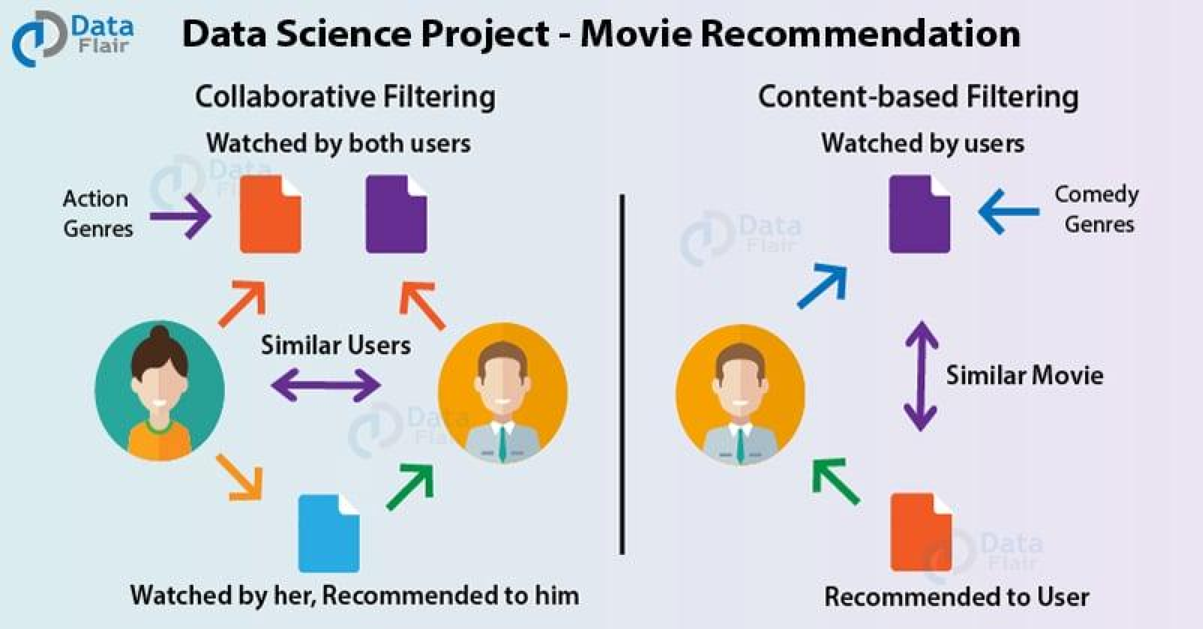
Data Science Movie Recommendation System Project in R

Have you ever been on an online streaming platform like Netflix, Amazon Prime, Voot? I watched a movie and after some time, that platform started recommending me different movies and TV shows. I wondered, how the movie streaming platform could suggest me content that appealed to me. Then I came across something known as Recommendation System. This system is capable of learning my watching patterns and providing me with relevant suggestions. Having witnessed the fourth industrial revolution where *Artificial Intelligence* and other technologies are dominating the market, I am sure that you must have come across a recommendation system in your everyday life. I am also sure that by this time curiosity must be getting the best of you. Therefore, in this Machine Learning Project, I will teach you to build your own recommendation system. So. let’s start.



Movie Recommendation System Project using ML

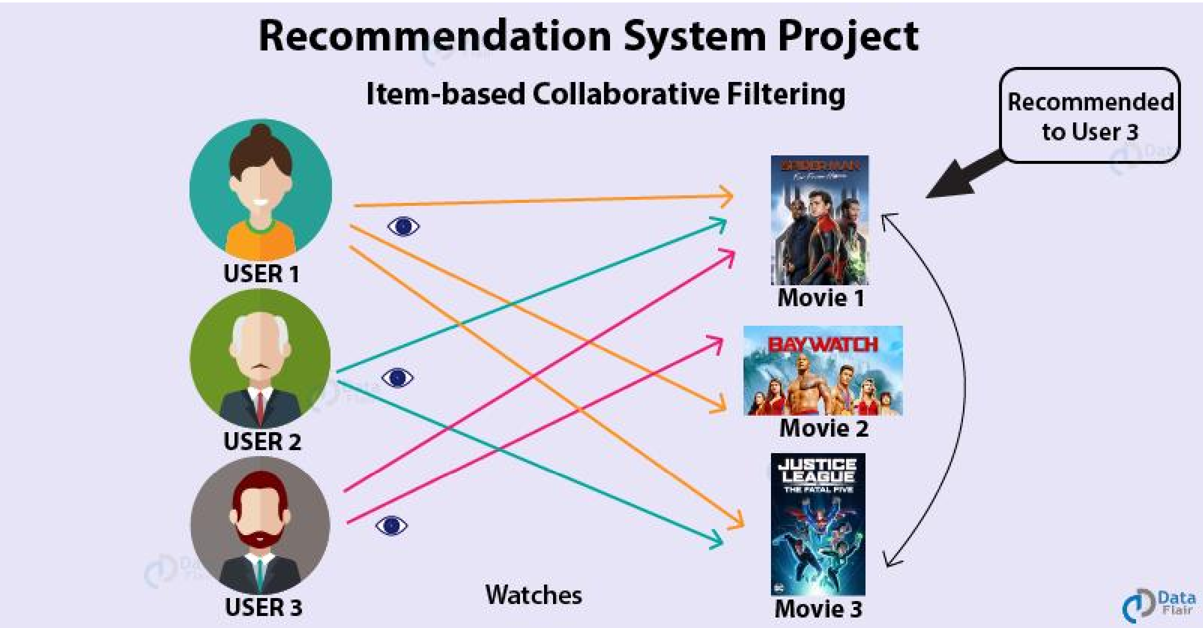
The main goal of this machine learning project is to build a recommendation engine that recommends movies to users. This R project is designed to help you understand the functioning of how a recommendation system works. We will be developing an Item Based Collaborative Filter. By the end of this tutorial, you will gain experience of implementing your R, Data Science, and *Machine learning skills* in a real-life project.

Before moving ahead in this movie recommendation system project in ML, you need to know what recommendation system means. Read below to find the answer.

What is a Recommendation System?

A recommendation system provides suggestions to the users through a filtering process that is based on user preferences and browsing history. The information about the user is taken as an input. The information is taken from the input that is in the form of browsing data. This information reflects the prior usage of the product as well as the assigned ratings. A recommendation system is a platform that provides its users with various contents based on their preferences and likings. A recommendation system takes the information about the user as an input. The recommendation system is an implementation of the

machine learning algorithms.



A recommendation system also finds a similarity between the different products. For example, Netflix Recommendation System provides you with the recommendations of the movies that are similar to the ones that have been watched in the past. Furthermore, there is a collaborative content filtering that provides you with the recommendations in respect with the other users who might have a similar viewing history or preferences. There are two types of recommendation systems – Content-Based Recommendation System and Collaborative Filtering Recommendation. In this project of recommendation system in R, we will work on a collaborative filtering recommendation system and more specifically, ITEM based collaborative recommendation system.

You must check [how Netflix recommendation engine works]

How to build a Movie Recommendation System using Machine Learning

Dataset

In order to build our recommendation system, we have used the MovieLens Dataset. You can find the movies.csv and ratings.csv file that we have used in our Recommendation System Project *[here]*. This data consists of 105339 ratings applied over 10329 movies.

Importing Essential Libraries

In our Data Science project, we will make use of these four packages – *'recommenderlab', 'ggplot2', 'data.table' and 'reshape2'.*

Code:

```
library(recommenderlab)
```

Output Screenshot:

```
library(recommenderlab)
```

```
## Loading required package: Matrix
```

```
## Loading required package: arules
```

```
##
## Attaching package: 'arules'
```

```
## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

```
## Loading required package: proxy
```

```
##
## Attaching package: 'proxy'
```

```
## The following object is masked from 'package:Matrix':
##
##     as.matrix
```

Code:

```
library(ggplot2)                              #Author DataFlair

library(data.table)

library(reshape2)
```

Output Screenshot:

```
library(ggplot2)                    #Author DataFlair
```

```
## Registered S3 methods overwritten by 'ggplot2':
##   method         from
##   [.quosures     rlang
##   c.quosures     rlang
##   print.quosures rlang
```

```
library(data.table)
library(reshape2)
```

```
##
## Attaching package: 'reshape2'
```

```
## The following objects are masked from 'package:data.table':
##
##     dcast, melt
```

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Retrieving the Data

We will now retrieve our data from movies.csv into movie_data dataframe and ratings.csv into rating_data. We will use the str() function to display information about the movie_data dataframe.

Code:

```
setwd("/home/dataflair/data/movie_data")                    #Author
DataFlair

movie_data <- read.csv("movies.csv",stringsAsFactors=FALSE)
```

```
rating_data <- read.csv("ratings.csv")

str(movie_data)
```

Output Screenshot:

```
setwd("/home/dataflair/data/movie_data")                    #Author DataFlair
movie_data <- read.csv("movies.csv",stringsAsFactors=FALSE)
rating_data <- read.csv("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 (1995)" ...
##  $ genres : chr  "Adventure|Animation|Children|Comedy|Fantasy" "Adventure|Childr
en|Fantasy" "Comedy|Romance" "Comedy|Drama|Romance" ...
```


We can overview the summary of the movies using the summary() function. We will also use the head() function to print the first six lines of movie_data

Code:

```
summary(movie_data)      #Author DataFlair
```

Output Screenshot:

```r
summary(movie_data)    #Author DataFlair
```

```
##     movieId          title              genres         
##  Min.   :     1   Length:10329       Length:10329      
##  1st Qu.:  3240   Class :character   Class :character  
##  Median :  7088   Mode  :character   Mode  :character  
##  Mean   : 31924                                        
##  3rd Qu.: 59900                                        
##  Max.   :149532
```

Code:

```r
head(movie_data)
```

Output Screenshot:

```r
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
```

Similarly, we can output the summary as well as the first six lines of the 'rating_data' dataframe –

Code:

```
summary(rating_data)    #Author DataFlair
```

Output Screenshot:

```
summary(rating_data)    #Author DataFlair
```

```
##      userId          movieId            rating         timestamp
##  Min.   :  1.0   Min.   :     1   Min.   :0.500   Min.   :8.286e+08
##  1st Qu.:192.0   1st Qu.:  1073   1st Qu.:3.000   1st Qu.:9.711e+08
##  Median :383.0   Median :  2497   Median :3.500   Median :1.115e+09
##  Mean   :364.9   Mean   : 13381   Mean   :3.517   Mean   :1.130e+09
##  3rd Qu.:557.0   3rd Qu.:  5991   3rd Qu.:4.000   3rd Qu.:1.275e+09
##  Max.   :668.0   Max.   :149532   Max.   :5.000   Max.   :1.452e+09
```

Code:

```
head(rating_data)
```

Output Screenshot:

```
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
```

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Data Pre-processing

From the above table, we observe that the userId column, as well as the movieId column, consist of integers. Furthermore, we need to convert the genres present in the movie_data dataframe into a more usable format by the users. In order to do so, we will first create a one-hot encoding to create a matrix that comprises of corresponding genres for each of the films.

Code:

```
movie_genre <- as.data.frame(movie_data$genres, stringsAsFactors=FALSE)

library(data.table)

movie_genre2 <- as.data.frame(tstrsplit(movie_genre[,1], '[|]',

                                   type.convert=TRUE),

                         stringsAsFactors=FALSE) #DataFlair

colnames(movie_genre2) <- c(1:10)

list_genre <- c("Action", "Adventure", "Animation", "Children",

               "Comedy", "Crime","Documentary", "Drama", "Fantasy",

               "Film-Noir", "Horror", "Musical", "Mystery","Romance",

               "Sci-Fi", "Thriller", "War", "Western")

genre_mat1 <- matrix(0,10330,18)

genre_mat1[1,] <- list_genre
```

```
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]) #Author
DataFlair

   genre_mat1[index+1,gen_col] <- 1

}

}

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

for (col in 1:ncol(genre_mat2)) {

 genre_mat2[,col] <- as.integer(genre_mat2[,col]) #convert from characters
to integers

}

str(genre_mat2)
```

Screenshot:

```r
movie_genre <- as.data.frame(movie_data$genres, stringsAsFactors=FALSE)
library(data.table)
movie_genre2 <- as.data.frame(tstrsplit(movie_genre[,1], '[|]',
                                   type.convert=TRUE),
                         stringsAsFactors=FALSE)     #DataFlair
colnames(movie_genre2) <- c(1:10)

list_genre <- c("Action", "Adventure", "Animation", "Children",
                "Comedy", "Crime","Documentary", "Drama", "Fantasy",
                "Film-Noir", "Horror", "Musical", "Mystery","Romance",
                "Sci-Fi", "Thriller", "War", "Western")
genre_mat1 <- matrix(0,10330,18)
genre_mat1[1,] <- list_genre
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])  #Author DataFlair
    genre_mat1[index+1,gen_col] <- 1
  }
}
genre_mat2 <- as.data.frame(genre_mat1[-1,], stringsAsFactors=FALSE) #remove first row, which was the genre list
for (col in 1:ncol(genre_mat2)) {
  genre_mat2[,col] <- as.integer(genre_mat2[,col])  #convert from characters to integers
}
str(genre_mat2)
```

Output –

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

In the next step of Data Pre-processing of R project, we will create a 'search matrix' that will allow us to perform an easy search of the films by specifying the genre present in our list.

Code:

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

head(SearchMatrix)     #DataFlair
```

Output Screenshot:

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

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

There are movies that have several genres, for example, Toy Story, which is an animated film also falls under the genres of Comedy, Fantasy, and Children. This applies to the majority of the films.

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

Code:

```
ratingMatrix <- 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
```

Output Screenshot:

```
ratingMatrix <- dcast(rating_data, userId~movieId, value.var = "rating", na.rm=F
ALSE)
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.
```

Are you facing any trouble in implementing recommendation system project in R? Comment below, DataFlair Team is ready to help you.

Let us now overview some of the important parameters that provide us various options for building recommendation systems for movies-

Code:

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

names(recommendation_model)
```

Output Screenshot:

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

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

Code:

```
lapply(recommendation_model, "[[", "description")
```

Output Screenshot:

```
lapply(recommendation_model, "[[", "description")
```

```
## $ALS_realRatingMatrix
## [1] "Recommender for explicit ratings based on latent factors, calculated by
alternating least squares algorithm."
##
## $ALS_implicit_realRatingMatrix
## [1] "Recommender for implicit data based on latent factors, calculated by alt
ernating least squares algorithm."
##
## $IBCF_realRatingMatrix
## [1] "Recommender based on item-based collaborative filtering."
##
## $POPULAR_realRatingMatrix
## [1] "Recommender based on item popularity."
##
```

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We will implement a single model in our R project – Item Based Collaborative Filtering.

Code:

```
recommendation_model$IBCF_realRatingMatrix$parameters
```

Output Screenshot:

```
recommendation_model$IBCF_realRatingMatrix$parameters
```

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

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.

Code:

```
similarity_mat <- similarity(ratingMatrix[1:4, ],

                              method = "cosine",

                              which = "users")

as.matrix(similarity_mat)

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

Output Screenshot:

```
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. We have taken four users and each cell in this matrix represents the similarity that is shared between the two users.

Now, we delineate the similarity that is shared between the films –

Code:

```
movie_similarity <- similarity(ratingMatrix[, 1:4], method =

                               "cosine", which = "items")

as.matrix(movie_similarity)

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

Output Screenshot:

```
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")
```

Let us now extract the most unique ratings –

```
rating_values <- as.vector(ratingMatrix@data)

unique(rating_values) # extracting unique ratings
```

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

Code:

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

Table_of_Ratings
```

Output Screenshot:

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

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

```r
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
## 6791761    1198    3258    1567    7943    5484   21729   12237   28880
##     4.5       5
##    8187   14856
```

This is the right time to check your R and Data Science Learning. Try these [latest interview questions] and become a pro.

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.

Code:

```r
library(ggplot2)

movie_views <- colCounts(ratingMatrix) # count views for each movie

table_views <- data.frame(movie = names(movie_views),

                          views = movie_views) # create dataframe of views

table_views <- table_views[order(table_views$views,
```

```
                                decreasing = TRUE), ] # sort by number of
views

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,]
```

Input Screenshot:

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

Output –

```
##     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, we will visualize a bar plot for the total number of views of the top films. We will carry this out using ggplot2.

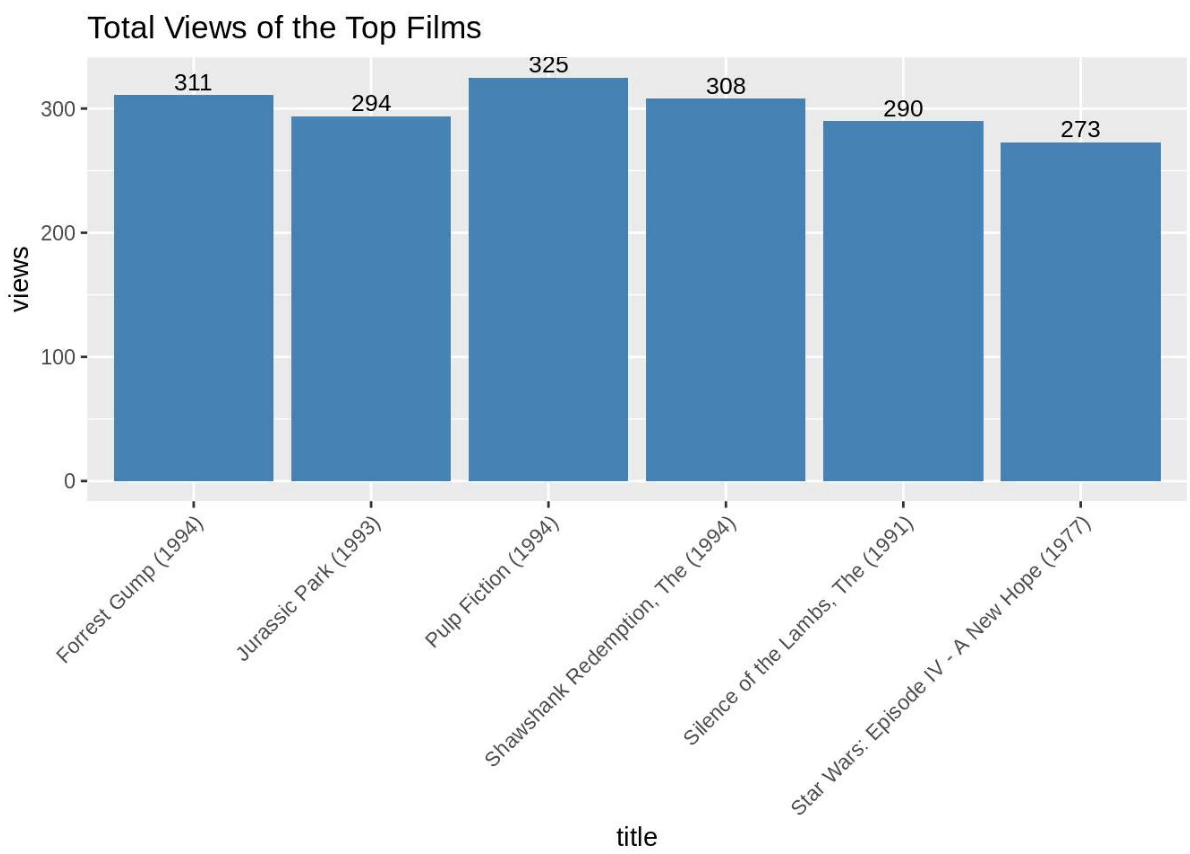
Code:

```
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")
```

Input Screenshot:

```
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")
```

Output:



From the above bar-plot, we observe that Pulp Fiction is the most-watched film followed by Forrest Gump.

If you are enjoying this Data Science Recommendation System Project, DataFlair brings another project for you – [Credit Card Fraud Detection using R](). Save the link, you can thank me later

Heatmap of Movie Ratings

Now, in this data science project of Recommendation system, we will visualize a heatmap of the movie ratings. This heatmap will contain first 25 rows and 25 columns as follows –

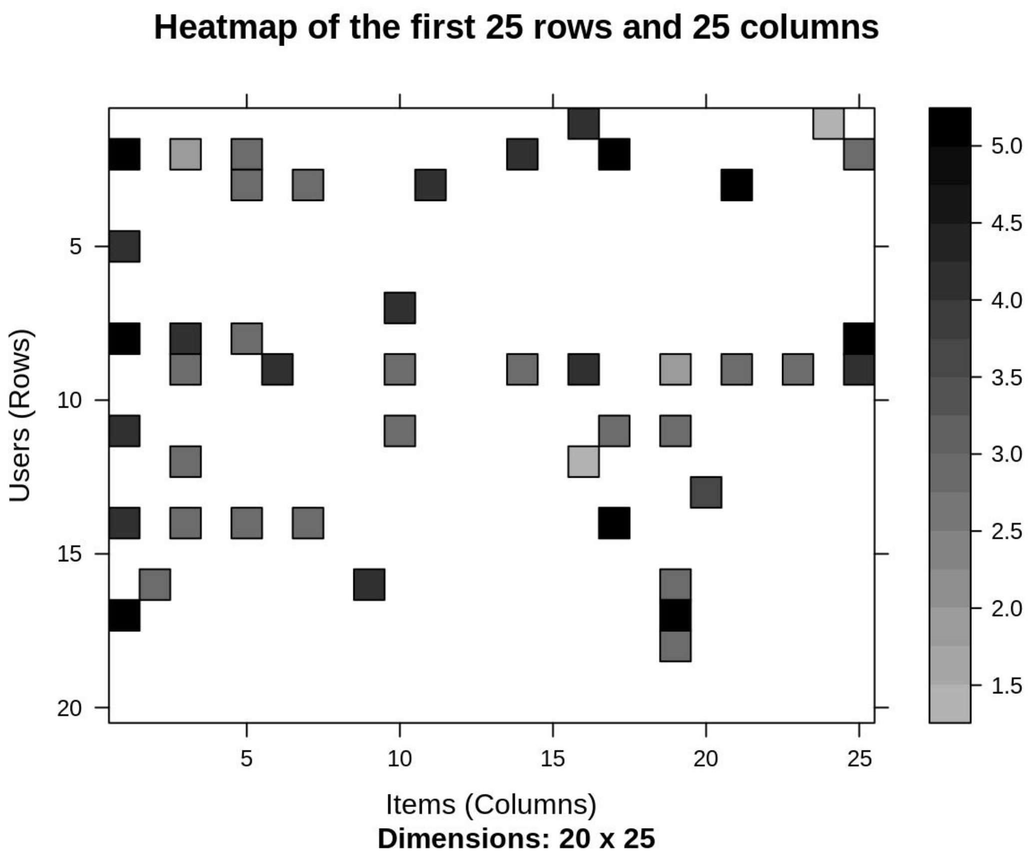
Code:

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

Input Screenshot:

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

Output:



Performing Data Preparation

We will conduct data preparation in the following three steps –

- Selecting useful data.
- Normalizing data.
- Binarizing the data.

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

Code:

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

Output Screenshot:

```
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 –

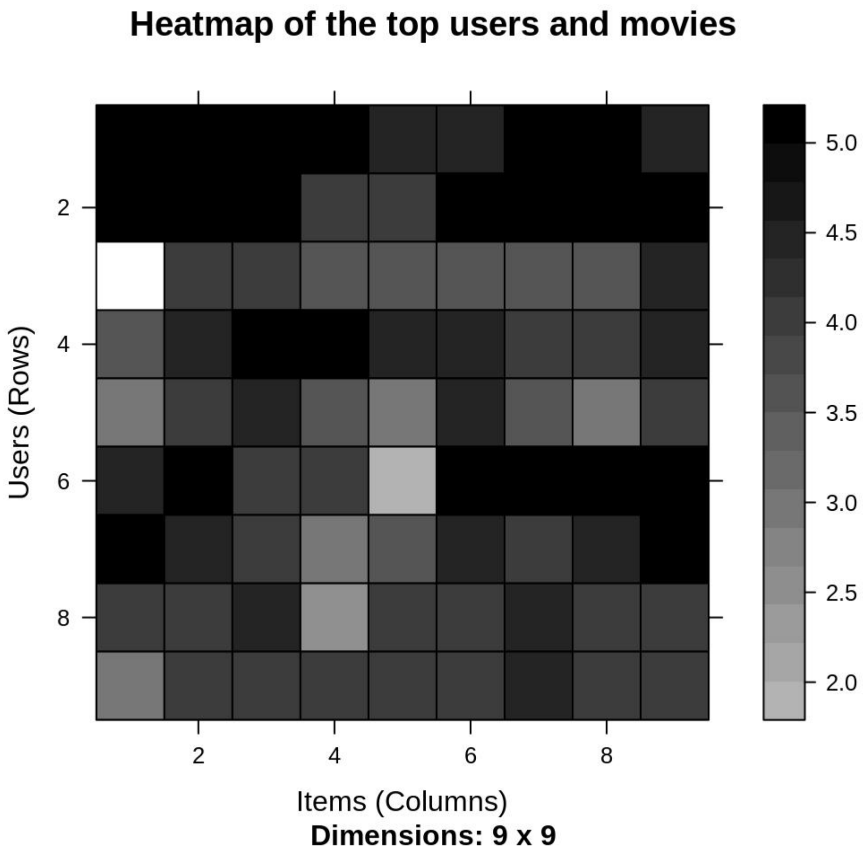
Code:

```
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")
```

Input Screenshot:

```
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")
```

Output:



[Data Visualization in R](#) – Learn the concepts in an easy way

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

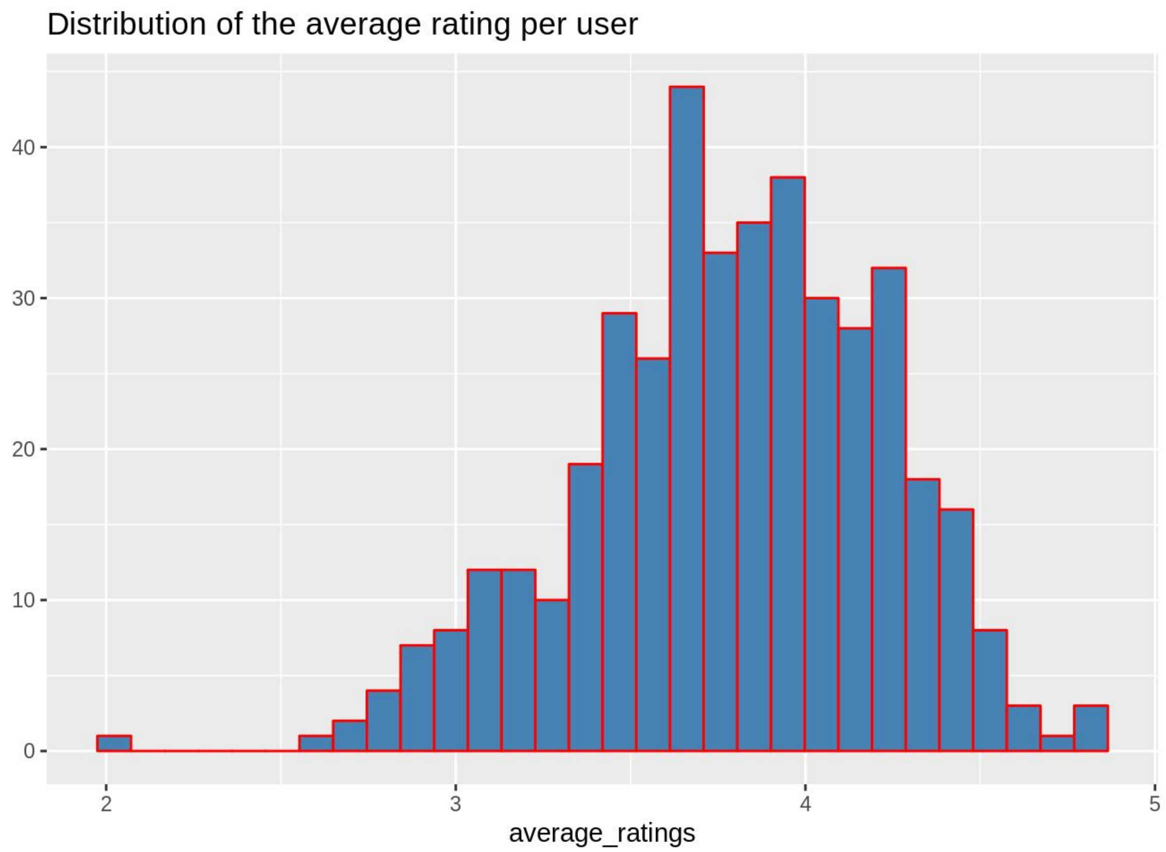
```
average_ratings <- rowMeans(movie_ratings)

qplot(average_ratings, fill=I("steelblue"), col=I("red")) +

 ggtitle("Distribution of the average rating per user")
```

Output Screenshot:

```
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`.
```

Output:



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 our model. In order to remove this, we normalize our 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.

Code:

```
normalized_ratings <- normalize(movie_ratings)

sum(rowMeans(normalized_ratings) > 0.00001)

image(normalized_ratings[rowCounts(normalized_ratings) > minimum_movies,

                         colCounts(normalized_ratings) > minimum_users],

main = "Normalized Ratings of the Top Users")
```

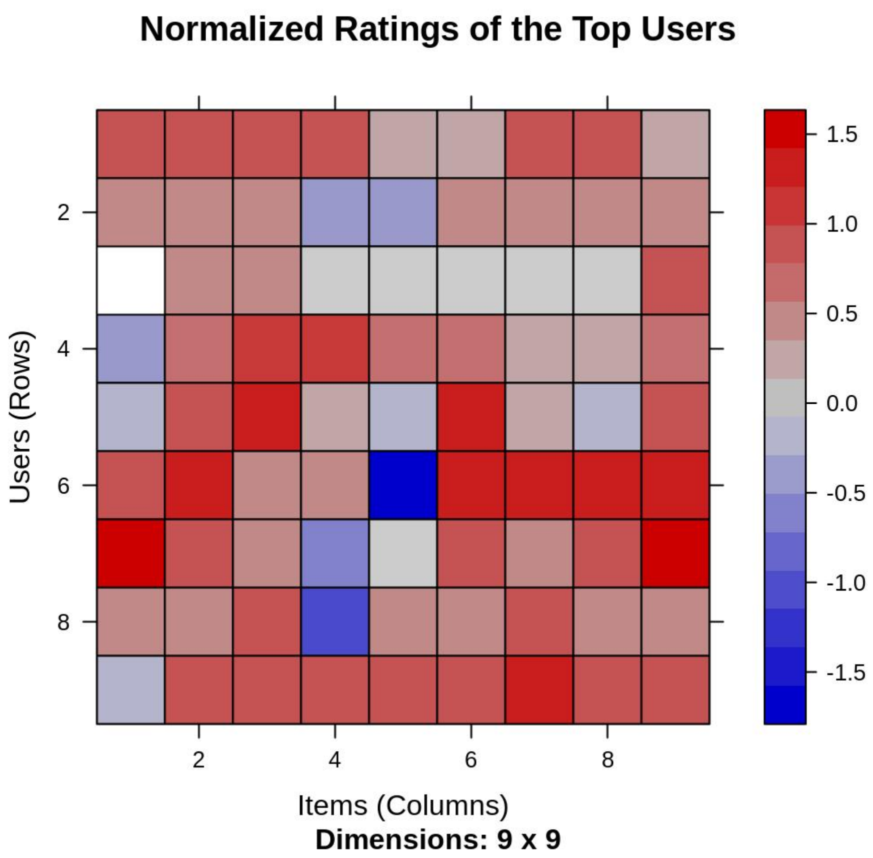
Output Screenshot:

```
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")
```

Output:



Performing Data Binarization

In the final step of our data preparation in this data science project, we will binarize our 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.

Code:

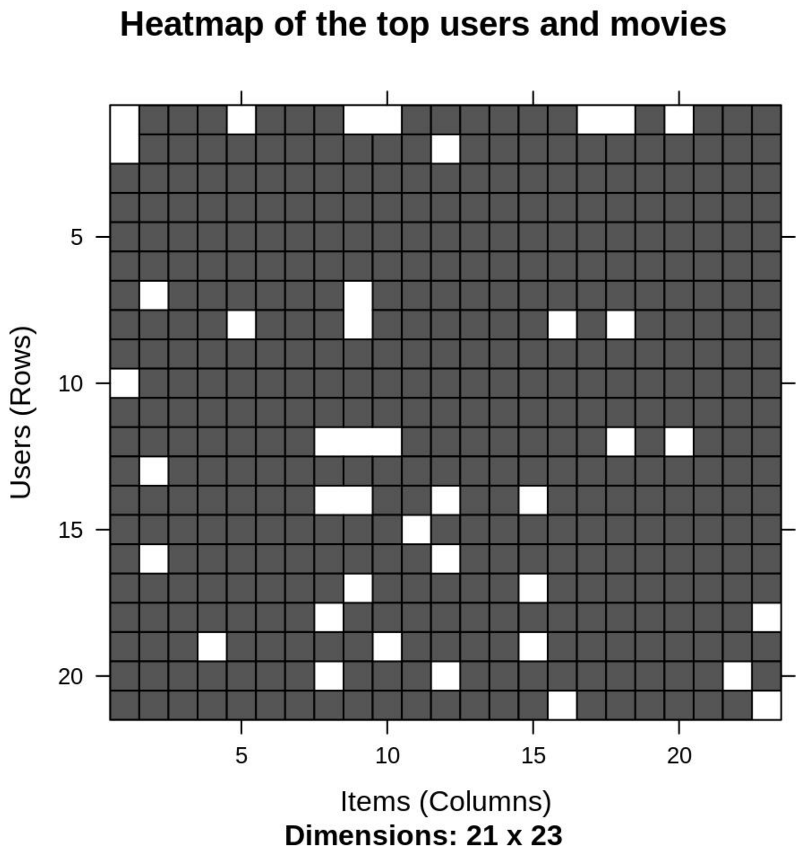
```
binary_minimum_movies <- quantile(rowCounts(movie_ratings), 0.95)

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")
```

Input Screenshot:

```
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")
```

Output:



Collaborative Filtering System

In this section of data science project, 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.

Code:

```
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, ]
```

Input Screenshot:

```
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 using R

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. We use the cosine method which is the default one but you can also use pearson method.

Code:

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

recommendation_system$IBCF_realRatingMatrix$parameters
```

Output Screenshot:

```
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
```

Code:

```
recommen_model <- Recommender(data = training_data,

                              method = "IBCF",

                              parameter = list(k = 30))

recommen_model

class(recommen_model)
```

Output Screenshot:

```
recommen_model <- Recommender(data = training_data,
                              method = "IBCF",
                              parameter = list(k = 30))
recommen_model
```

```
## Recommender of type 'IBCF' for 'realRatingMatrix'
## learned using 337 users.
```

```
class(recommen_model)
```

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

Let us now explore our data science recommendation system model as follows –

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.

Code:

```
model_info <- getModel(recommen_model)

class(model_info$sim)

dim(model_info$sim)

top_items <- 20

image(model_info$sim[1:top_items, 1:top_items],

  main = "Heatmap of the first rows and columns")
```

Output Screenshot:

```
model_info <- getModel(recommen_model)

class(model_info$sim) # this contains a similarity matrix
```

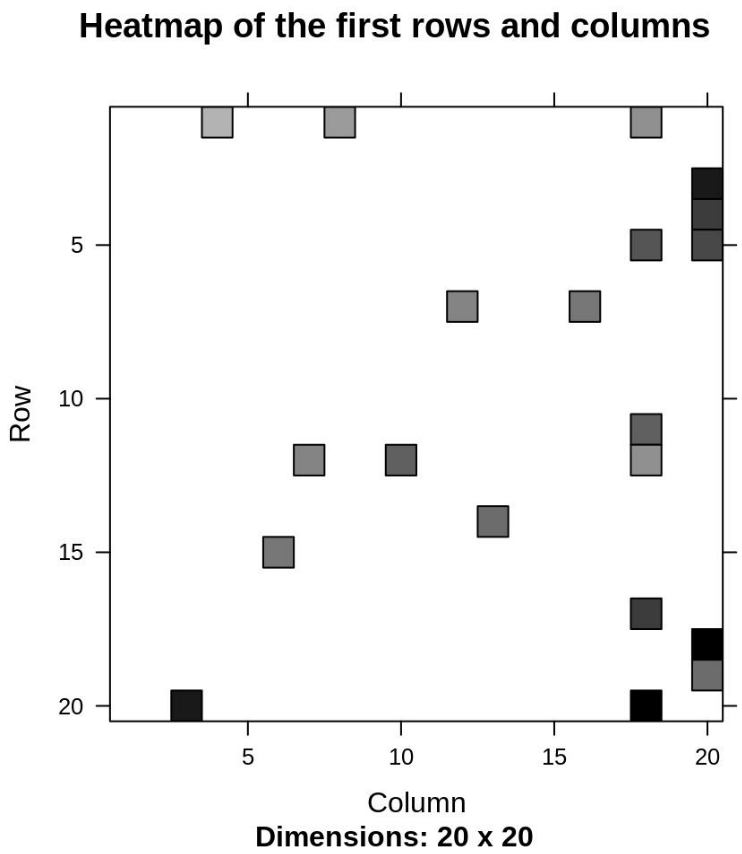
```
## [1] "dgCMatrix"
## attr(,"package")
## [1] "Matrix"
```

```
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")
```

Output:



In the next step of ML project, 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 –

Code:

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

table(sum_rows)
```

```
sum_cols <- colSums(model_info$sim > 0)

qplot(sum_cols, fill=I("steelblue"), col=I("red"))+ ggtitle("Distribution
of the column count")
```

Output Screenshot:

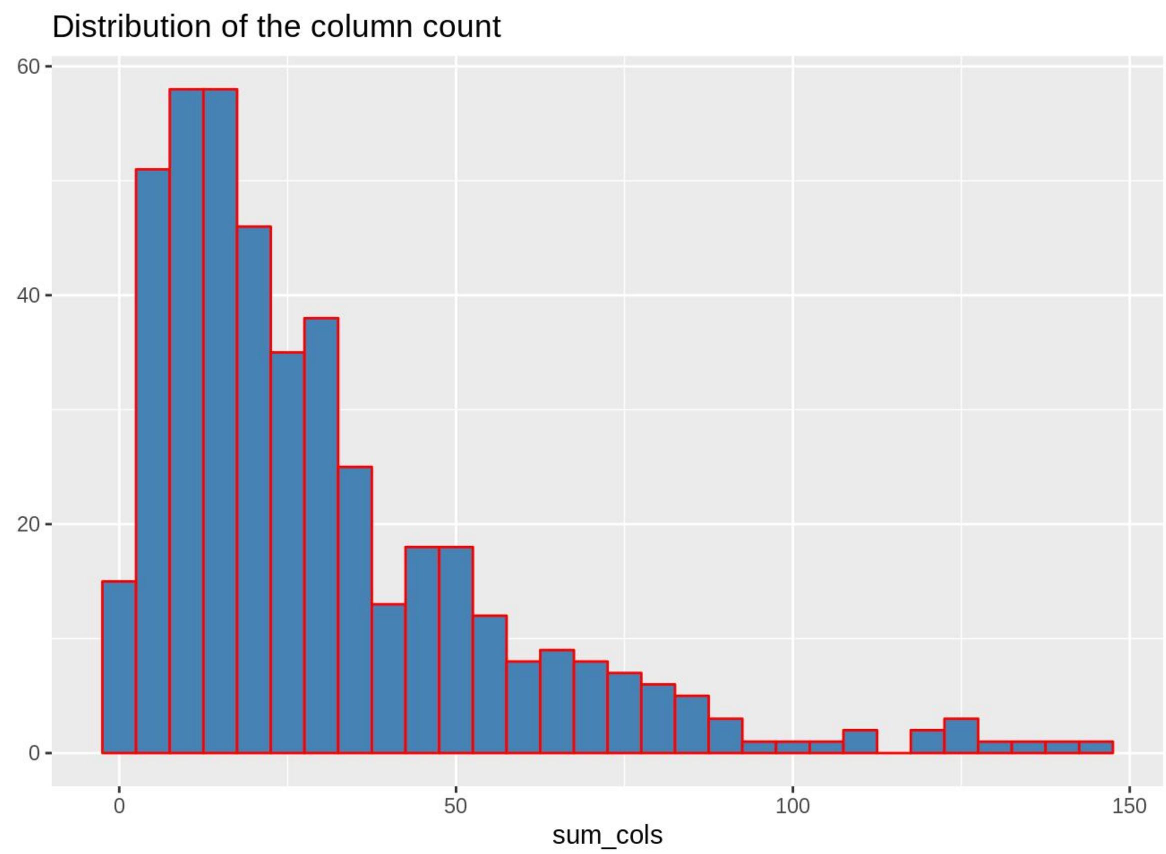
```
sum_rows <- rowSums(model_info$sim > 0)
table(sum_rows)
```

```
## 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`.
```

Output:



How to build Recommender System on dataset using R?

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.

Code:

```
top_recommendations <- 10 # the number of items to recommend to each user
```

```
predicted_recommendations <- predict(object = recommen_model,

                                     newdata = testing_data,

                                     n = top_recommendations)

predicted_recommendations
```

Output Screenshot:

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

```
## Recommendations as 'topNList' with n = 10 for 83 users.
```

Code:

```
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
```

Output Screenshot:

```
user1 <- predicted_recommendations@items[[1]] # recommendation for the first use
r
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$movieId == movies_user1[inde
x])$title)
}
movies_user2
```

Output:

```
##  [1] "Broken Arrow (1996)"
##  [2] "Species (1995)"
##  [3] "Mask, The (1994)"
##  [4] "Executive Decision (1996)"
##  [5] "Annie Hall (1977)"
##  [6] "Little Miss Sunshine (2006)"
##  [7] "Pan's Labyrinth (Laberinto del fauno, El) (2006)"
##  [8] "Hangover, The (2009)"
##  [9] "Mrs. Doubtfire (1993)"
## [10] "Leaving Las Vegas (1995)"
```

Code:

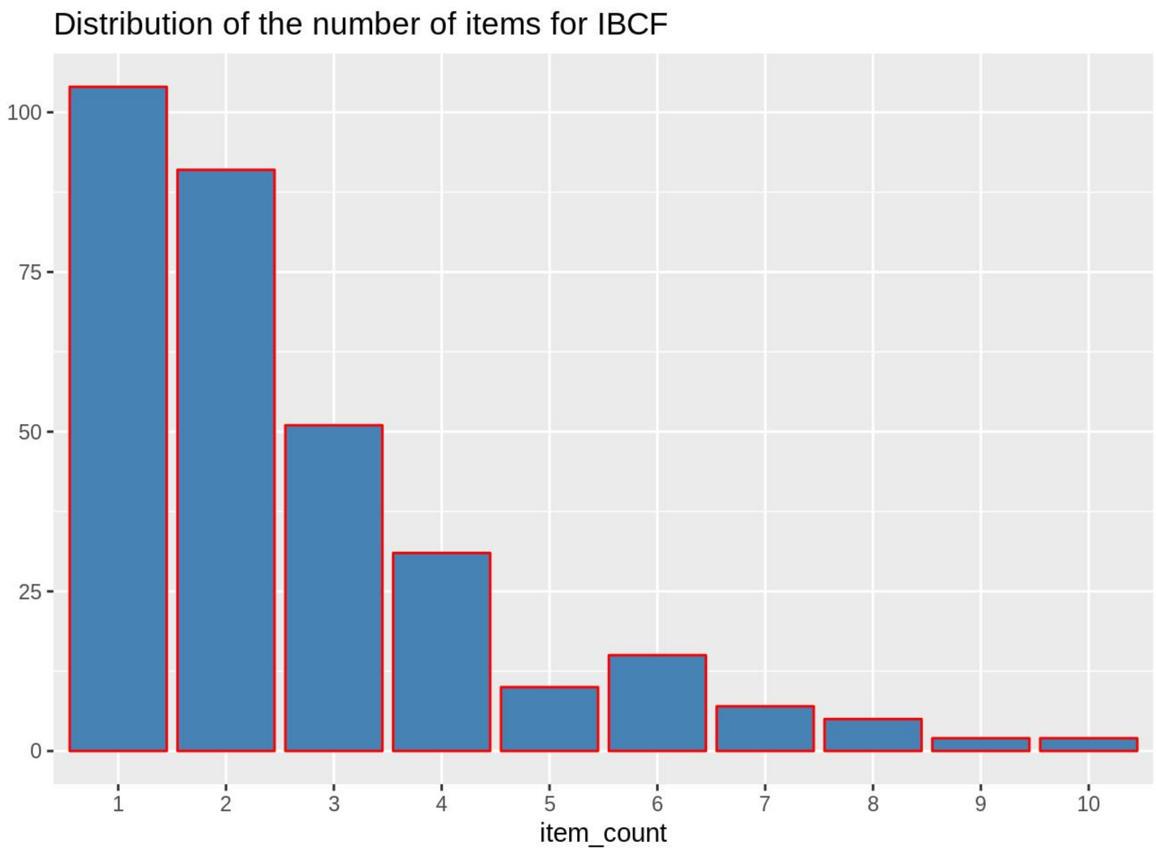
```
recommendation_matrix <- sapply(predicted_recommendations@items,

                    function(x){ as.integer(colnames(movie_ratings)[x]) })
# matrix with the recommendations for each user

#dim(recc_matrix)

recommendation_matrix[,1:4]
```

Output Screenshot:

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

```
##       [,1] [,2] [,3] [,4]
##  [1,]    95    7 1748  145
##  [2,]   196  145 2321 1517
##  [3,]   367  163  145  163
##  [4,]   494  265  141 2005
##  [5,]  1230  339  435 4896
##  [6,] 46578  350 4022  160
##  [7,] 48394  355 5218  420
##  [8,] 69122  370  474 2671
```

Output:



Output:

```
##                                  Movie title No of items
## 21                         Get Shorty (1995)          10
## 145                          Bad Boys (1995)          10
## 19  Ace Ventura: When Nature Calls (1995)           9
## 34                               Babe (1995)           9
```

Summary

Recommendation Systems are the most popular type of machine learning applications that are used in all sectors. They are an improvement over the traditional classification algorithms as they can take many classes of input and provide similarity ranking based algorithms to provide the user with accurate results. These recommendation systems have evolved over time and have incorporated many advanced machine learning techniques to provide the users with the content that they want