HarvardX: PH125.9x Data Science – Capstone Project: MovieLens

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Introduction

This capstone project creating a movie recommendation system using the MovieLens dataset. Also to predicts the movie rating by machine learning algorithm using the inputs in one subset in the validation set. The dataset used for this purpose can be found in the following links

- [MovieLens 10M dataset] https://grouplens.org/datasets/movielens/10m/
- [MovieLens 10M dataset - zip file] http://files.grouplens.org/datasets/movielens/ml-10m.zip

The goal of this project is:

- To create a movie recommendation system
- To reduce the RMSE less than 0.8649

Read the data

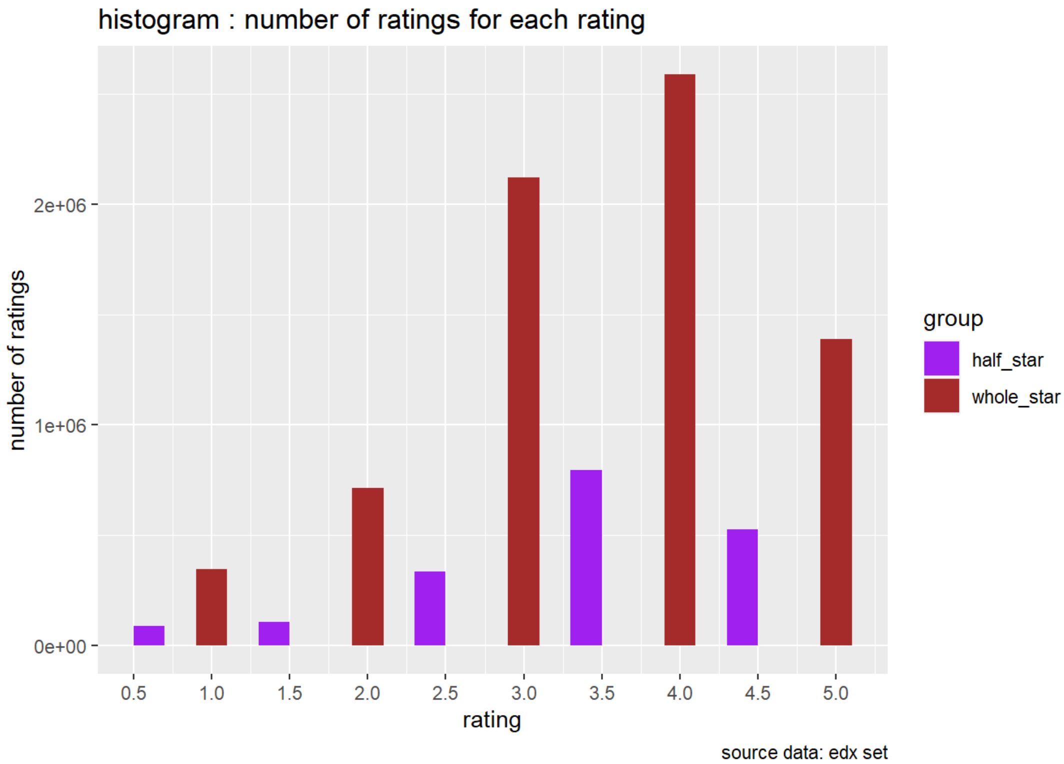
```
library(tidyverse)

library(caret)

dl <- tempfile()
download.file("http://files.grouplens.org/datasets/movielens/ml-10m.zip", dl)

ratings <- read.table(text = gsub("::", "\t", readLines(unzip(dl, "ml-10M100K
/ratings.dat"))),
                      col.names = c("userId", "movieId", "rating", "timestamp
"))

movies <- str_split_fixed(readLines(unzip(dl, "ml-10M100K/movies.dat")), "\\:
:", 3)
colnames(movies) <- c("movieId", "title", "genres")
movies <- as.data.frame(movies) %>% mutate(movieId = as.numeric(movieId),
                                           title = as.character(title),
                                           genres = as.character(genres))

movielens <- left_join(ratings, movies, by = "movieId")
```

```r
# Validation set will be 10% of MovieLens data

set.seed(1)
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, l
ist = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]

# Make sure userId and movieId in validation set are also in edx set

validation <- temp %>%
     semi_join(edx, by = "movieId") %>%
     semi_join(edx, by = "userId")

# Add rows removed from validation set back into edx set

removed <- anti_join(temp, validation)

## Joining, by = c("userId", "movieId", "rating", "timestamp", "title", "genr
es")
```

DATA EXPLORATION

```r
summary(edx)

##      userId         movieId          rating        timestamp
##  Min.   :    1   Min.   :    1   Min.   :0.500   Min.   :7.897e+08
##  1st Qu.:18122   1st Qu.:  648   1st Qu.:3.000   1st Qu.:9.468e+08
##  Median :35743   Median : 1834   Median :4.000   Median :1.035e+09
##  Mean   :35869   Mean   : 4120   Mean   :3.512   Mean   :1.033e+09
##  3rd Qu.:53602   3rd Qu.: 3624   3rd Qu.:4.000   3rd Qu.:1.127e+09
##  Max.   :71567   Max.   :65133   Max.   :5.000   Max.   :1.231e+09
##     title              genres
##  Length:9000047     Length:9000047
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##

#A new dataframe "explore_ratings" is created which contains half star and wh
ole star ratings  from the edx set :

group <-  ifelse((edx$rating == 1 |edx$rating == 2 | edx$rating == 3 |
                  edx$rating == 4 | edx$rating == 5) ,
                   "whole_star",
                   "half_star")

explore_ratings <- data.frame(edx$rating, group)
```

```r
# Plot the explore_ratings dataframe via histogram

ggplot(explore_ratings, aes(x= edx.rating, fill = group)) +
  geom_histogram( binwidth = 0.2) +
  scale_x_continuous(breaks=seq(0, 5, by= 0.5)) +
  scale_fill_manual(values = c("half_star"="purple", "whole_star"="brown")) +
  labs(x="rating", y="number of ratings", caption = "source data: edx set") +
  ggtitle("histogram : number of ratings for each rating")
```



Exploring ratings of the edx set , we notice the following facts:

1. The average user’s activity reveals that no user gives 0 as rating

2. The top 5 ratings from most to least are : 4, 3, 5, 3.5 and 2.

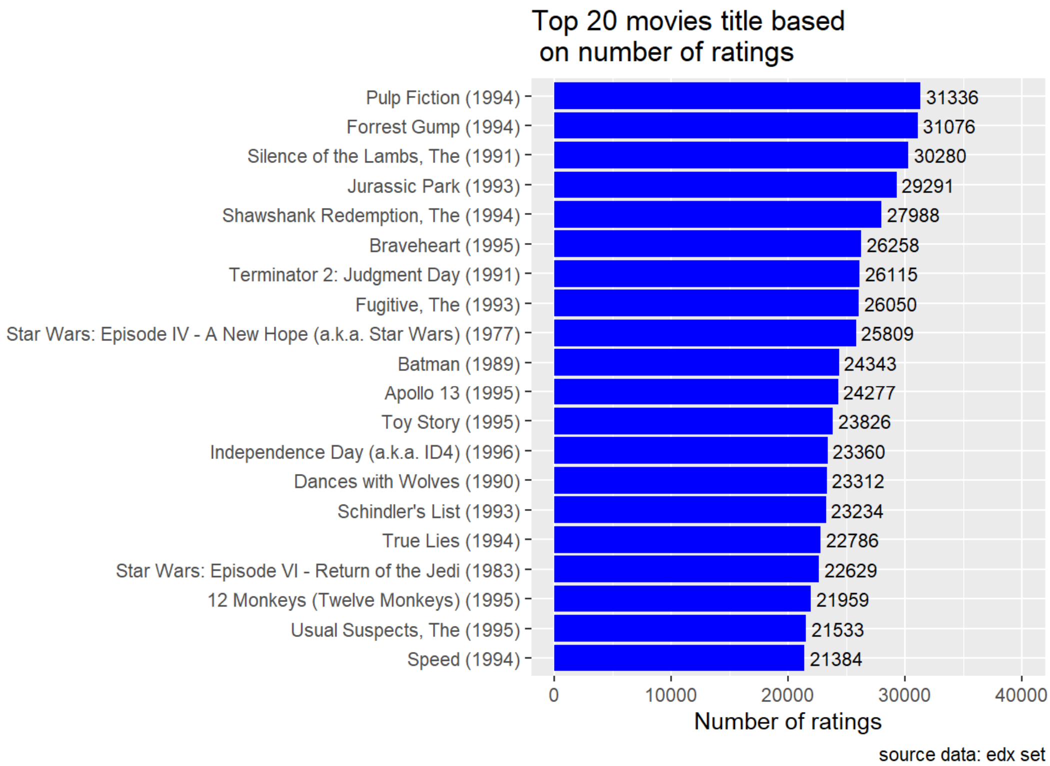
3. The histogram shows that the half star ratings are less common than whole star ratings.

Exploring the features “genres” and “title” of our edx set.

```r
#bar chart of top_title

top_title <- edx %>%
  group_by(title) %>%
  summarize(count=n()) %>%
  top_n(20,count) %>%
  arrange(desc(count))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
top_title %>%
  ggplot(aes(x=reorder(title, count), y=count)) +
  geom_bar(stat='identity', fill="blue") + coord_flip(y=c(0, 40000)) +
  labs(x="", y="Number of ratings") +
  geom_text(aes(label= count), hjust=-0.1, size=3) +
  labs(title="Top 20 movies title based \n on number of ratings" , caption =
"source data: edx set")
```

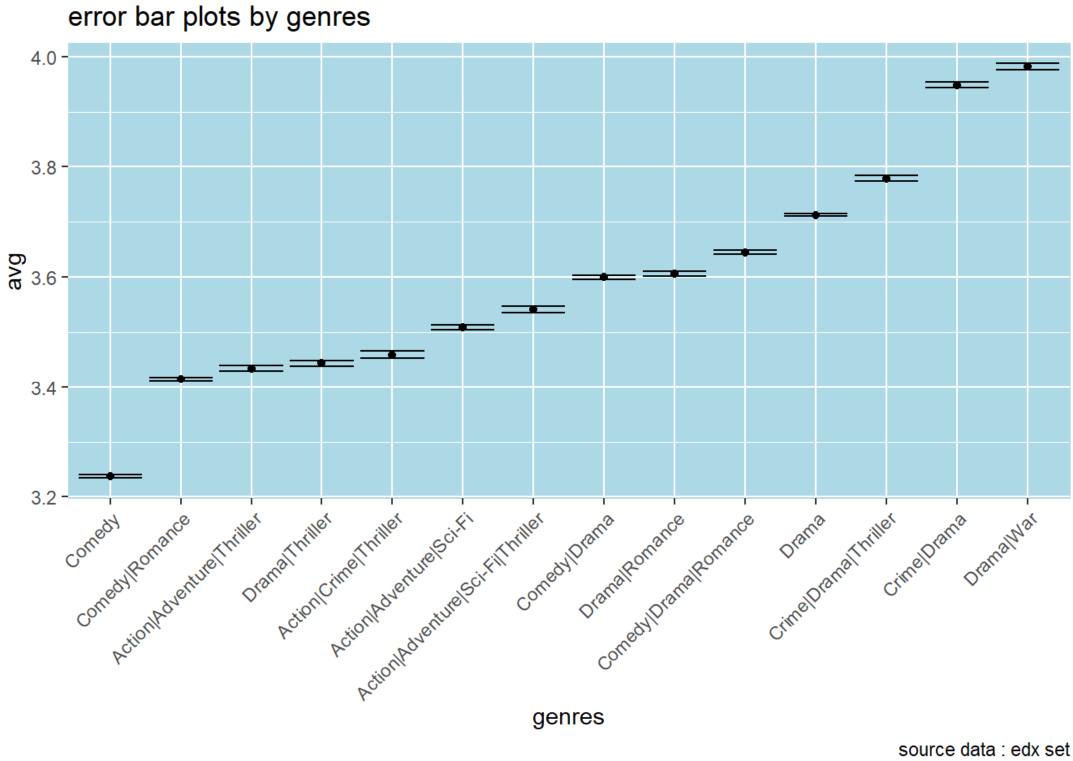


The movies which have the highest number of ratings are in the top genres categories : movies like Pulp fiction (1994), Forrest Gump(1994) or Jurrasic Park(1993) which are in the top 5 of movie's ratings number , are part of the Drama, Comedy or Action genres.

```
#Computing the average and standard error for each "genre" , plotting the eff
ect of genre
edx %>% group_by(genres) %>%
  summarize(n = n(), avg = mean(rating), se = sd(rating)/sqrt(n())) %>%
  filter(n >= 100000) %>%
  mutate(genres = reorder(genres, avg)) %>%
  ggplot(aes(x = genres, y = avg, ymin = avg - 2*se, ymax = avg + 2*se)) +
  geom_point() +
  geom_errorbar() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(title = "error bar plots by genres" , caption = "source data : edx set
```

```
") +
  theme(
    panel.background = element_rect(fill = "lightblue",
                                    colour = "lightblue",
                                    size = 0.5, linetype = "solid"),
    panel.grid.major = element_line(size = 0.5, linetype = 'solid',
                                    colour = "white"),
    panel.grid.minor = element_line(size = 0.25, linetype = 'solid',
                                    colour = "white")
  )
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

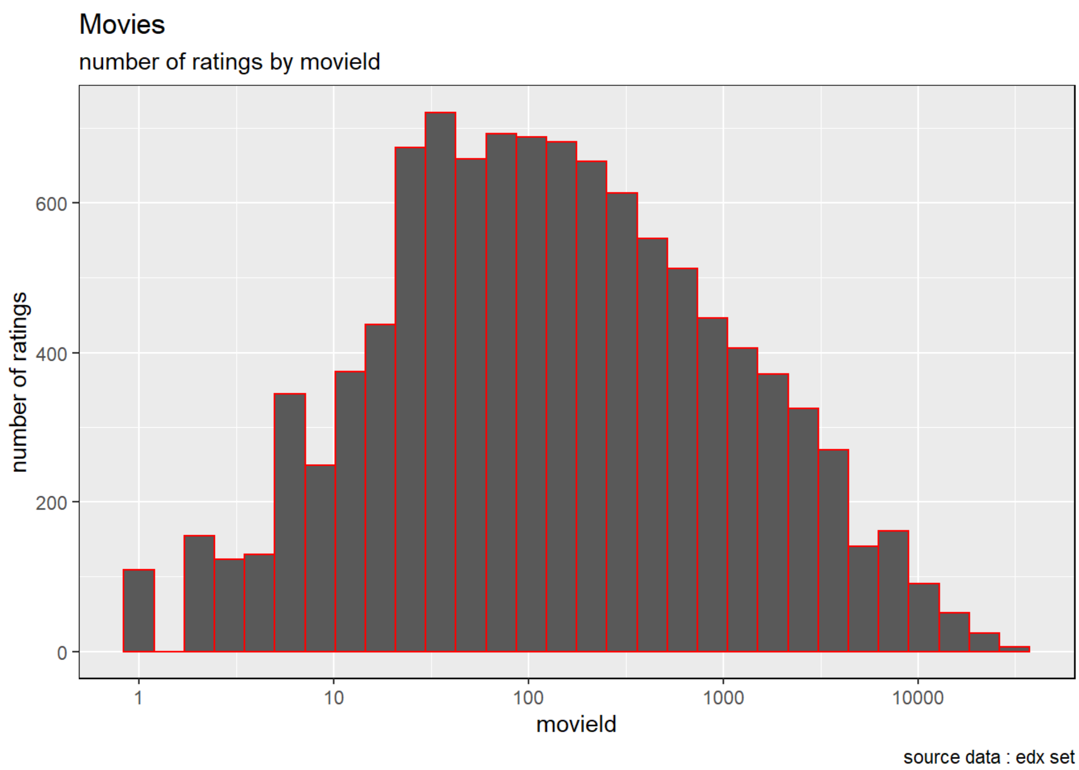


We observe that the generated plot shows strong evidence of a genre effect.

```
edx %>%
  summarize(n_users = n_distinct(userId),
            n_movies = n_distinct(movieId))
```

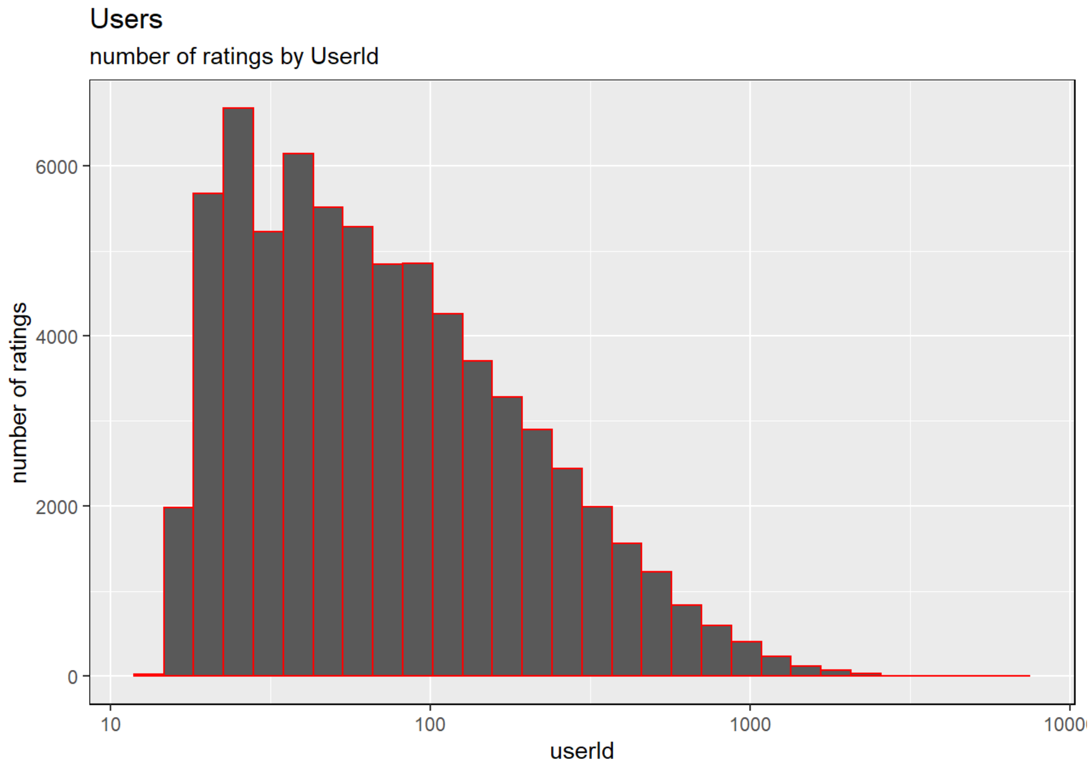
Even if each row represents a rating given by one user to one movie, the number of unique values for the userId is 69878 and for the movieId 10664 : Both usersId and movieId which are presented as integer should be presumably treat as factors for some analysis purposes. Also, this means that there are less movies provided for ratings than users that rated them. If we think in terms of a large matrix, with user on the rows and movies on the columns, a challenge we face is the sparsity of our matrix. This large matrix will contain many empty cells. Moreover, we face a curse of dimensionality problem .These issues should be treat in our further analysis.

```
# histogram of number of ratings by movieId

edx %>%
  count(movieId) %>%
  ggplot(aes(n)) +
  geom_histogram( bins=30, color = "red") +
  scale_x_log10() +
  ggtitle("Movies") +
  labs(subtitle  ="number of ratings by movieId",
       x="movieId" ,
       y="number of ratings",
       caption ="source data : edx set") +
  theme(panel.border = element_rect(colour="black", fill=NA))
```




```
edx %>%
  count(userId) %>%
  ggplot(aes(n)) +
  geom_histogram( bins=30, color = "red") +
  scale_x_log10() +
  ggtitle("Users") +
  labs(subtitle ="number of ratings by UserId",
       x="userId" ,
```

```
      y="number of ratings") +
  theme(panel.border = element_rect(colour="black", fill=NA))
```



DATA PREPROCESSING Data typically needs to be preprocessed (e.g. cleansed, filtered, transformed) in order to be used by the machine learning techniques in the analysis step.

1. <u>Data transformation: Building a rating matrix</u>

```
#Using SparseMatrix function to get the rating matrix from Matrix package
library(Matrix)

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

edx_1 <- edx

edx_1$userId <- as.factor(edx_1$userId)
edx_1$movieId <- as.factor(edx_1$movieId)

edx_1$userId <- as.numeric(edx_1$userId)
edx_1$movieId <- as.numeric(edx_1$movieId)
sparse_ratings <- sparseMatrix(i = edx_1$userId,
                         j = edx_1$movieId ,
```

```
                                    x = edx_1$rating,
                                    dims = c(length(unique(edx_1$userId)),
                                             length(unique(edx_1$movieId))),
                                    dimnames = list(paste("u", 1:length(unique(edx_1$use
rId)), sep = ""),
                                                   paste("m", 1:length(unique(edx_1$movi
eId)), sep = "")))


# remove the copy created
rm(edx_1)

#give a look on the first 10 users
sparse_ratings[1:10,1:10]

## 10 x 10 sparse Matrix of class "dgCMatrix"

##    [[ suppressing 10 column names 'm1', 'm2', 'm3' ... ]]

##
## u1  . .   . . . . . . . .
## u2  . .   . . . . . . . .
## u3  . .   . . . . . . . .
## u4  . .   . . . . . . . .
## u5  1 .   . . . . 3 . . .
## u6  . .   . . . . . . . .
## u7  . .   . . . . . . . .
## u8  . 2.5 . . 3 4 . . . .
## u9  . .   . . . . . . . .
## u10 . .   . . . . 3 . . .

class(sparse_ratings)

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

#Convert rating matrix into a recommenderlab sparse matrix via recommenderlab
package
library(recommenderlab)

ratingMat <- new("realRatingMatrix", data = sparse_ratings)
ratingMat

## 69878 x 10664 rating matrix of class 'realRatingMatrix' with 9000047 ratin
gs.
```

2. Relevant Data

We know that some users saw more movies than the others. So, instead of displaying some random users and movies, we should select the most relevant users and movies. Thus we visualize only the users who have seen many movies and the movies that have been seen by many users. To identify and select the most relevant users and movies, we follow these steps:

1. Determine the minimum number of movies per user.

2. Determine the minimum number of users per movie.

3. Select the users and movies matching these criteria.

```
min_n_movies <- quantile(rowCounts(ratingMat), 0.9)

min_n_users <- quantile(colCounts(ratingMat), 0.9)


ratings_movies <- ratingMat[rowCounts(ratingMat) > min_n_movies,
                            colCounts(ratingMat) > min_n_users]
```

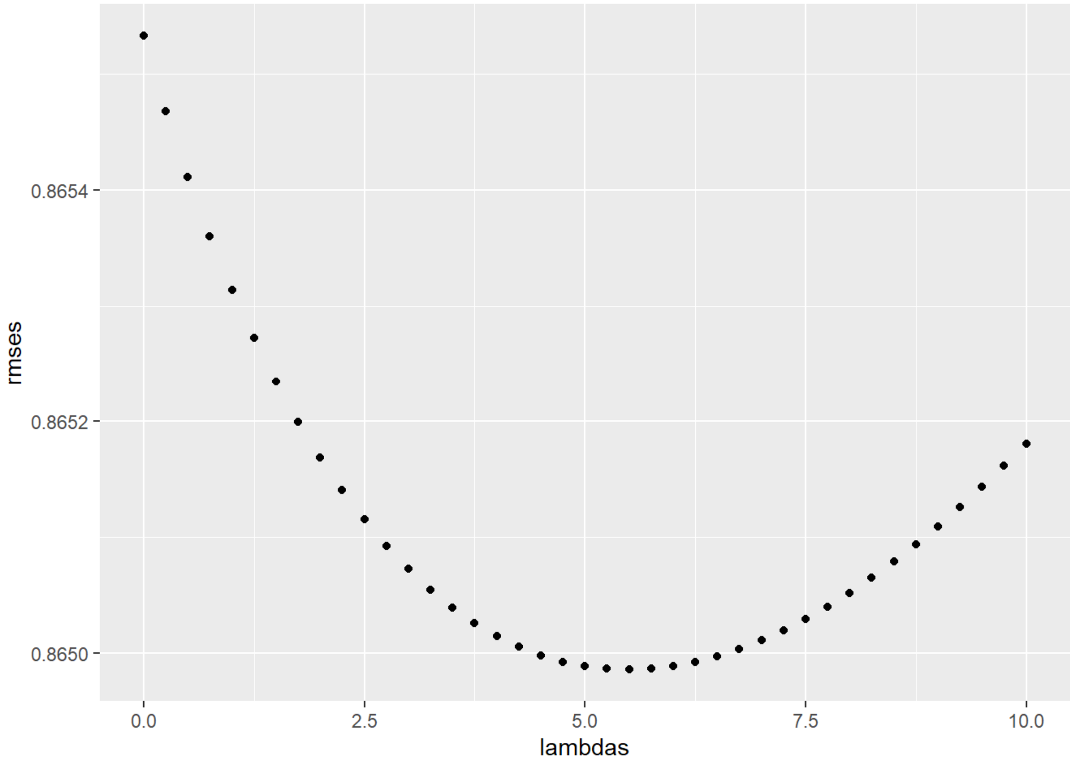
we can notice that now, we have a rating matrix of 6976 distinct users (rows) x 1067 distinct movies(columns) , with 2311476 ratings .

```
#before to proceed with regularization, i just remove the object copy of vali
dation, "valid"
rm(valid)
```

```
## Warning in rm(valid): object 'valid' not found
```

```
#e. regularization

# remembering (5), $\lambda$ is a tuning parameter. We can use cross-validati
on to choose it


lambdas <- seq(0, 10, 0.25)

  rmses <- sapply(lambdas, function(l){

    mu_reg <- mean(edx$rating)

    b_i_reg <- edx %>%
      group_by(movieId) %>%
      summarize(b_i_reg = sum(rating - mu_reg)/(n()+l))

    b_u_reg <- edx %>%
      left_join(b_i_reg, by="movieId") %>%
      group_by(userId) %>%
      summarize(b_u_reg = sum(rating - b_i_reg - mu_reg)/(n()+l))

    predicted_ratings_b_i_u <-
      validation %>%
```

```
      left_join(b_i_reg, by = "movieId") %>%
      left_join(b_u_reg, by = "userId") %>%
      mutate(pred = mu_reg + b_i_reg + b_u_reg) %>%
      .$pred

    return(RMSE(validation$rating,predicted_ratings_b_i_u))
  })

  qplot(lambdas, rmses)
```




```
lambda <- lambdas[which.min(rmses)]
lambda

## [1] 5.5

#valid_set
mu <- mean(edx$rating)
b_i_reg <- edx %>%
    group_by(movieId) %>%
    summarize(b_i = sum(rating - mu)/(n()+lambda))

## `summarise()` ungrouping output (override with `.groups` argument)

b_u_reg <- edx %>%
    left_join(b_i_reg, by="movieId") %>%
    group_by(userId) %>%
    summarize(b_u = sum(rating - b_i - mu)/(n()+lambda))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
predicted_ratings_6 <-
    validation %>%
    left_join(b_i_reg, by = "movieId") %>%
    left_join(b_u_reg, by = "userId") %>%
    mutate(pred = mu + b_i + b_u) %>%
    pull(pred)
View(predicted_ratings_6)
model_6_rmse <- RMSE(predicted_ratings_6, validation$rating) # 0.864818
```

Methods and Analysis Recommender Engines

```
# a. POPULAR , UBCF and IBCF algorithms of the recommenderlab package
library(recommenderlab)
model_pop <- Recommender(ratings_movies, method = "POPULAR",
                      param=list(normalize = "center"))

#prediction example on the first 10 users
pred_pop <- predict(model_pop, ratings_movies[1:10], type="ratings")
as(pred_pop, "matrix")[,1:10]
```

```
##            m1       m2       m3       m5       m6       m7       m9       m
10
## u8   3.845709       NA 2.908521       NA       NA 3.091285 2.524774 3.3150
59
## u17        NA       NA 3.012617       NA 3.860392       NA 2.628869       
NA
## u28        NA       NA       NA       NA 3.167586 2.502576       NA 2.7263
50
## u30        NA       NA       NA 2.800736       NA 3.118312 2.551801       
NA
## u43  4.693015 3.793565 3.755826 3.621014 4.603602       NA 3.372079 4.1623
65
## u48        NA       NA       NA 3.505851 4.488439 3.823428 3.256917       
NA
## u57        NA       NA 2.646955 2.512143 3.494730 2.829720 2.263208 3.0534
93
## u70  4.426355 3.526905 3.489166 3.354354 4.336941 3.671931 3.105419 3.8957
04
## u88        NA 3.040854 3.003116 2.868303       NA 3.185880 2.619368 3.4096
54
## u103       NA 2.819650 2.781912 2.647099       NA 2.964676 2.398164 3.1884
50
##           m11      m14
## u8   3.452896 3.411770
## u17        NA 3.515866
## u28  2.864186 2.823060
## u30        NA 3.438797
## u43        NA 4.259075
## u48  4.185039 4.143913
```

```
## u57        NA 3.150204
## u70  4.033541 3.992415
## u88  3.547490 3.506365
## u103 3.326286       NA

#Calculation of rmse for popular method
e <- evaluationScheme(ratings_movies, method="split", train=0.7, given=-5)
#5 ratings of 30% of users are excluded for testing

model_pop <- Recommender(getData(e, "train"), "POPULAR")

prediction_pop <- predict(model_pop, getData(e, "known"), type="ratings")

rmse_popular <- calcPredictionAccuracy(prediction_pop, getData(e, "unknown"))
[1]
rmse_popular

##      RMSE
## 0.8470042

#Estimating rmse for UBCF using Cosine similarity and selected n as 50 based
on cross-validation
set.seed(1)
model <- Recommender(getData(e, "train"), method = "UBCF",
                     param=list(normalize = "center", method="Cosine", nn=50)
)

prediction <- predict(model, getData(e, "known"), type="ratings")

rmse_ubcf <- calcPredictionAccuracy(prediction, getData(e, "unknown"))[1]
rmse_ubcf

##      RMSE
## 0.8320826

#Estimating rmse for IBCF using Cosine similarity and selected n as 350 based
on cross-validation
set.seed(1)

model_ibcf <- Recommender(getData(e, "train"), method = "IBCF",
                     param=list(normalize = "center", method="Cosine", k=350)
)

prediction_ibcf <- predict(model_ibcf, getData(e, "known"), type="ratings")

rmse_ibcf <- calcPredictionAccuracy(prediction_ibcf, getData(e, "unknown"))[1
]
rmse_ibcf
```

```
##       RMSE
## 0.9569868
```

```
#summarize all the rmse for recommender algorithms
library(kableExtra)

rmse_results <- data.frame(methods=c("Regularized Movie + User Effect Model",
"Recommender Popular Model" , "Recommender UBCF" ,"Recommender IBCF"),rmse =
c(model_6_rmse, rmse_popular,rmse_ubcf,rmse_ibcf))

kable(rmse_results) %>%
  kable_styling(bootstrap_options = "striped" , full_width = F , position = "
center") %>%
  kable_styling(bootstrap_options = "bordered", full_width = F , position ="c
enter") %>%
  column_spec(1,bold = T ) %>%
  column_spec(2,bold = T ,color = "white" , background ="#D7261E")
```

Methods	**RMSE**
Regularized Movie + User Effect Model	0.8649855
Recommender Popular Model	0.8470042
Recommender UBCF	0.8320826
Recommender IBCF	0.9569868