Movie Recommendation System using MovieLens data

Dibyajyoti Sarkar

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```
knitr::opts_chunk$set(message = FALSE, echo = TRUE)
```

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

Overview

This project is related to the MovieLens Project of the HarvardX: PH125.9x Data Science: Capstone project The present report starts with a general idea of the project and by representing its objective.

Then the given dataset will be prepared and setup. An exploratory data analysis is carried out in order to develop a machine learning algorithm that could predict movie ratings until a final model. Results will be explained. Finally the report ends with some concluding remarks.

Introduction

Recommendation systems use ratings that users have given to items to make specific recommendations. Companies that sell many products to many customers and permit these customers to rate their products, like Amazon, are able to collect massive datasets that can be used to predict what rating a particular user will give to a specific item. Items for which a high rating is predicted for a given user are then recommended to that user.

The same could be done for other items, as movies for instance in our case. Recommendation systems are one of the most used models in machine learning algorithms. In fact the success of Netflix is said to be based on its strong recommendation system. The Netflix prize (open competition for the best collaborative filtering algorithm to predict user ratings for films, based on previous ratings without any other information about the users or films), in fact, represent the high importance of algorithm for products recommendation system.

For this project we will focus on create a movie recommendation system using the 10M version of MovieLens dataset, collected by GroupLens Research.

Github - "https://github.com/dj-sarkar/movielens"

Aim of the project

The aim in this project is to train a machine learning algorithm that predicts user ratings (from 0.5 to 5 stars) using the inputs of a provided subset.

The value used to evaluate algorithm performance is the Root Mean Square Error, or RMSE. RMSE is one of the most used measure of the differences between values predicted by a model and the values observed. RMSE is a measure of accuracy, to compare forecasting errors of different models for a particular dataset, a lower RMSE is better than a higher one. The effect of each error on RMSE is proportional to the size of the

squared error; thus larger errors have a disproportionately large effect on RMSE. Consequently, RMSE is sensitive to outliers. The evaluation criteria for this algorithm is a RMSE expected to be lower than 0.8775.

The best resulting model will be used to predict the movie ratings.

Dataset

The MovieLens dataset is automatically downloaded

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

```
##################################################################
# Create edx set, validation set, and submission file
##################################################################
# Note: this process could take a couple of minutes for loading required package:
# tidyverse and package caret
if(!require(tidyverse)) install.packages("tidyverse",
                                         repos = "http://cran.us.r-project.org")
if(!require(caret)) install.packages("caret",
                                     repos = "http://cran.us.r-project.org")
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(levels(movieId))[movieId],
                                           title = as.character(title),
                                           genres = as.character(genres))
movielens <- left_join(ratings, movies, by = "movieId")
```

In order to predict in the most possible accurate way the movie rating of the users that haven't seen the movie yet, the MovieLens dataset will be split into 2 subsets that will be the "edx", a training subset to train the algorithm, and "validation" a subset to test the movie ratings.

```
# The Validation subset will be 10% of the MovieLens data.
set.seed(1)
test_index <- createDataPartition(y = movielens$rating,
                                  times = 1, p = 0.1, list = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]
#Make sure userId and movieId in validation set are also in edx subset:
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)
edx <- rbind(edx, removed)
rm(dl, ratings, movies, test_index, temp, movielens, removed)


# Loading the file
#edx <- readRDS("edx.rds")

# Summary of the edx dataset confirms no missing values
summary(edx)
```

```
##      userId         movieId          rating        timestamp
##  Min.   :    1   Min.   :    1   Min.   :0.500   Min.   :7.897e+08
##  1st Qu.:18124   1st Qu.:  648   1st Qu.:3.000   1st Qu.:9.468e+08
##  Median :35738   Median : 1834   Median :4.000   Median :1.035e+09
##  Mean   :35870   Mean   : 4122   Mean   :3.512   Mean   :1.033e+09
##  3rd Qu.:53607   3rd Qu.: 3626   3rd Qu.:4.000   3rd Qu.:1.127e+09
##  Max.   :71567   Max.   :65133   Max.   :5.000   Max.   :1.231e+09
##     title              genres
##  Length:9000055     Length:9000055
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##
```

```
# First entries of the edx dataset. The subset contain the
# six variables "userID", "movieID", "rating", "timestamp", "title", and "genres".
# Each row represent a single rating of a user for a single movie.
head(edx)
```

```
##   userId movieId rating timestamp                         title
## 1      1     122      5 838985046              Boomerang (1992)
## 2      1     185      5 838983525               Net, The (1995)
## 4      1     292      5 838983421               Outbreak (1995)
## 5      1     316      5 838983392               Stargate (1994)
## 6      1     329      5 838983392 Star Trek: Generations (1994)
## 7      1     355      5 838984474       Flintstones, The (1994)
##                           genres
## 1                Comedy|Romance
## 2          Action|Crime|Thriller
## 4  Action|Drama|Sci-Fi|Thriller
## 5        Action|Adventure|Sci-Fi
## 6 Action|Adventure|Drama|Sci-Fi
## 7        Children|Comedy|Fantasy
```

```
# Checking the edx dataset properties. The total of unique movies and users in
# the edx subset is about 70.000 unique users and about 10.700 different movies
n_distinct(edx$movieId)
```

```
## [1] 10677
```

```r
n_distinct(edx$genres)
```

```
## [1] 797
```

```r
n_distinct(edx$userId)
```

```
## [1] 69878
```

```r
nrow(edx)
```

```
## [1] 9000055
```

```r
# Loading the file
#validation <- readRDS("validation.rds")

# Summary of the validation dataset
summary(validation)
```

```
##      userId         movieId          rating        timestamp
##  Min.   :    1   Min.   :    1   Min.   :0.500   Min.   :7.897e+08
##  1st Qu.:18096   1st Qu.:  648   1st Qu.:3.000   1st Qu.:9.467e+08
##  Median :35768   Median : 1827   Median :4.000   Median :1.035e+09
##  Mean   :35870   Mean   : 4108   Mean   :3.512   Mean   :1.033e+09
##  3rd Qu.:53621   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:999999      Length:999999
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##
```

```r
# First entries of the validation dataset
head(validation)
```

```
##   userId movieId rating timestamp
## 1      1     231      5 838983392
## 2      1     480      5 838983653
## 3      1     586      5 838984068
## 4      2     151      3 868246450
## 5      2     858      2 868245645
## 6      2    1544      3 868245920
##                                                 title
## 1                                   Dumb & Dumber (1994)
## 2                                   Jurassic Park (1993)
## 3                                      Home Alone (1990)
## 4                                         Rob Roy (1995)
## 5                                    Godfather, The (1972)
## 6 Lost World: Jurassic Park, The (Jurassic Park 2) (1997)
```

```
##                                     genres
## 1                                     Comedy
## 2        Action|Adventure|Sci-Fi|Thriller
## 3                           Children|Comedy
## 4                 Action|Drama|Romance|War
## 5                              Crime|Drama
## 6 Action|Adventure|Horror|Sci-Fi|Thriller
```

```
# Checking the validation dataset properties
n_distinct(validation$movieId)
```

```
## [1] 9809
```

```
n_distinct(validation$genres)
```

```
## [1] 773
```

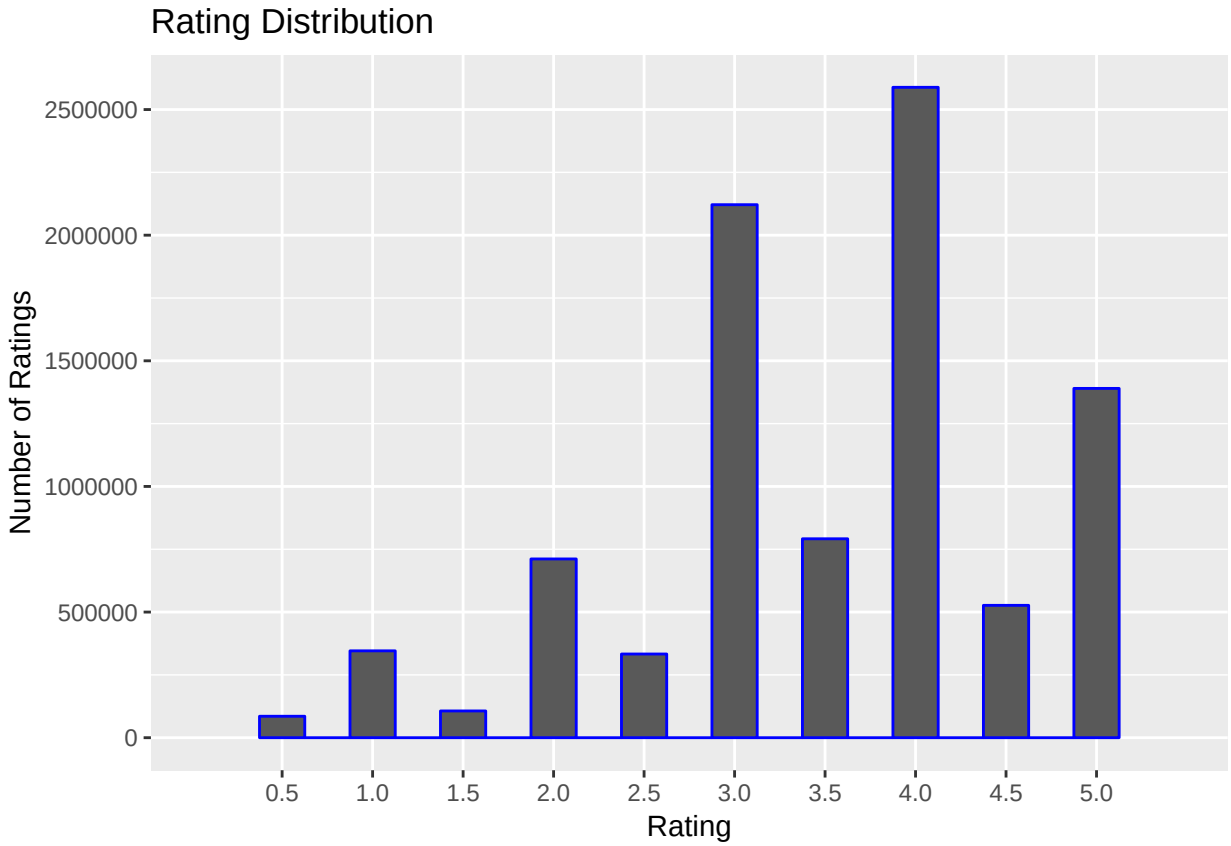
```
n_distinct(validation$userId)
```

```
## [1] 68534
```

```
nrow(validation)
```

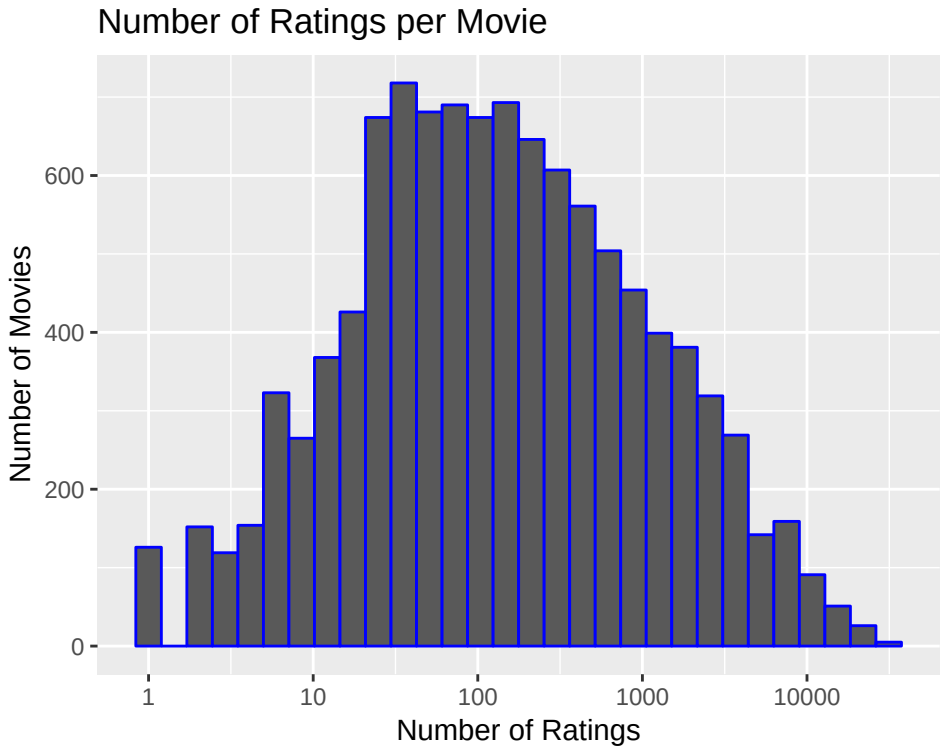
```
## [1] 999999
```

Users have a preference to rate movies rather higher than lower as shown by the distribution of ratings below. 4 is the most common rating, followed by 3 and 5. 0.5 is the least common rating. In general, half rating are less common than whole star ratings.



Some movies have been rated much often than others, while some have very few ratings and sometimes even only one rating. This will be important for our model as very low rating numbers might results in untrustworthy estimate for our predictions. Almost 125 movies have been rated only once.

```
edx %>%
count(movieId) %>%
ggplot(aes(n)) +
geom_histogram(bins = 30, color = "blue") +
scale_x_log10() +
xlab("Number of Ratings") +
  ylab("Number of Movies") +
ggtitle("Number of Ratings per Movie")
```



Some 20 movies were rated only once and appear to be obscure, predictions of future ratings for them will be difficult.

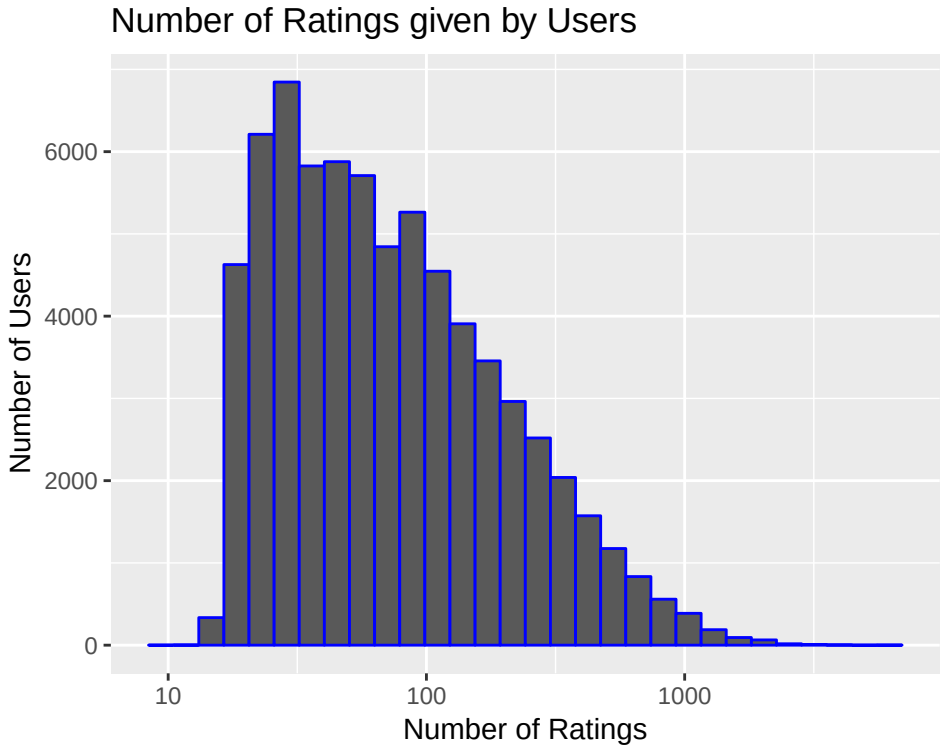
```
edx %>%
  group_by(movieId) %>%
  summarize(count = n()) %>%
  filter(count == 1) %>%
  left_join(edx, by = "movieId") %>%
  group_by(title) %>%
  summarize(rating = rating, n_rating = count) %>%
  slice(1:20) %>%
  knitr::kable()
```

title	rating	n_rating
1, 2, 3, Sun (Un, deuz, trois, soleil) (1993)	2.0	1
100 Feet (2008)	2.0	1
4 (2005)	2.5	1
Accused (Anklaget) (2005)	0.5	1
Ace of Hearts (2008)	2.0	1
Ace of Hearts, The (1921)	3.5	1
Adios, Sabata (Indio Black, sai che ti dico: Sei un gran figlio di...) (1971)	1.5	1
Africa addio (1966)	3.0	1
Aleksandra (2007)	3.0	1
Bad Blood (Mauvais sang) (1986)	4.5	1
Battle of Russia, The (Why We Fight, 5) (1943)	3.5	1
Bellissima (1951)	4.0	1
Big Fella (1937)	3.0	1
Black Tights (1-2-3-4 ou Les Collants noirs) (1960)	3.0	1
Blind Shaft (Mang jing) (2003)	2.5	1

title	rating	n_rating
Blue Light, The (Das Blaue Licht) (1932)	5.0	1
Borderline (1950)	3.0	1
Brothers of the Head (2005)	2.5	1
Chapayev (1934)	1.5	1
Cold Sweat (De la part des copains) (1970)	2.5	1

One can observe that the majority of users have rated between 30 and 100 movies. So, a user penalty term needs to be included later in our models.

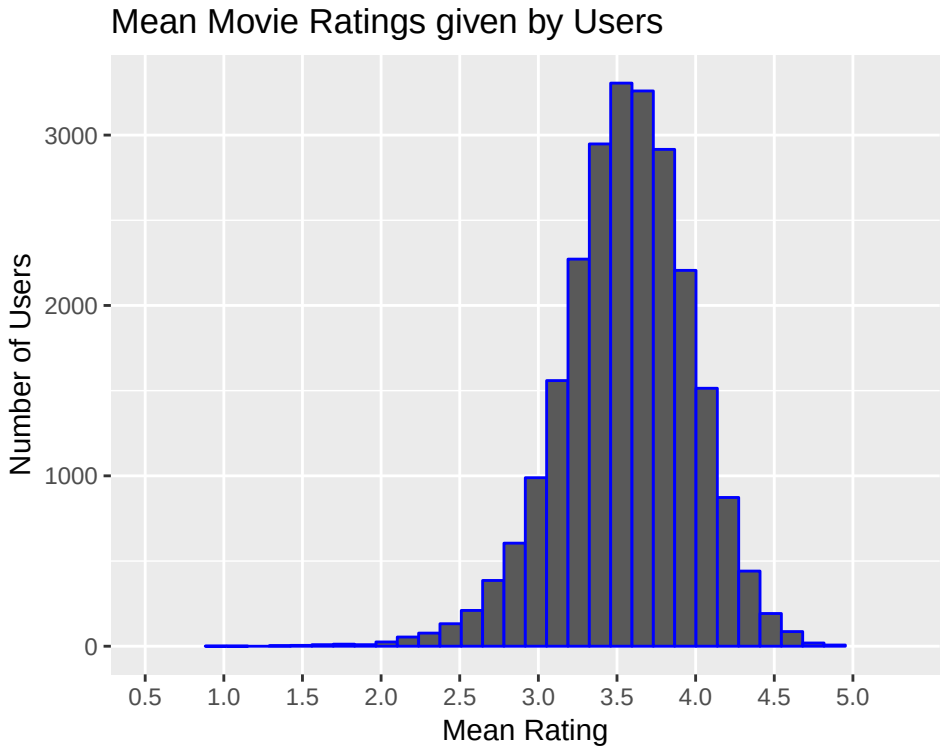
```
edx %>%
count(userId) %>%
ggplot(aes(n)) +
geom_histogram(bins = 30, color = "blue") +
scale_x_log10() +
xlab("Number of Ratings") +
ylab("Number of Users") +
ggtitle("Number of Ratings given by Users")
```



Furthermore, users differ vastly in how critical they are with their ratings. Some users tend to give much lower star ratings and some users tend to give higher star ratings than average. The visualization below includes only users that have rated at least 100 movies.

```
edx %>%
  group_by(userId) %>%
  filter(n() >= 100) %>%
  summarize(b_u = mean(rating)) %>%
  ggplot(aes(b_u)) +
```

```
  geom_histogram(bins = 30, color = "blue") +
  xlab("Mean Rating") +
  ylab("Number of Users") +
  ggtitle("Mean Movie Ratings given by Users") +
  scale_x_discrete(limits = c(seq(0.5,5,0.5)))
```



Modelling Approach

The loss-function, that computes the RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{u,i}(\hat{y}_{u,i} - y_{u,i})^2}$$

with N being the number of user/movie combinations and the sum occurring over all these combinations. The RMSE is our measure of model accuracy.

The written function to compute the RMSE for vectors of ratings and their corresponding predictions is:

```
RMSE <- function(true_ratings, predicted_ratings){
  sqrt(mean((true_ratings - predicted_ratings)^2))
}
```

1. Average Movie Rating Model

The first model predicts the same rating for all movies, so we compute the dataset's mean rating. The expected rating of the underlying data set is between 3 and 4. We start by building the simplest possible

recommender system by predicting the same rating for all movies regardless of user who give it. A model based approach assumes the same rating for all movie with all differences explained by random variation :

$$Y_{u,i} = \mu + \epsilon_{u,i}$$

with $\epsilon_{u,i}$ independent error sample from the same distribution centered at 0 and μ the "true" rating for all movies. This very simple model makes the assumption that all differences in movie ratings are explained by random variation alone. The estimate that minimizes the RMSE is the least square estimate of $Y_{u,i}$, in this case, is the average of all ratings: The expected rating of the underlying data set is between 3 and 4.

```
mu <- mean(edx$rating)
mu
```

```
## [1] 3.512465
```

If we predict all unknown ratings with μ or mu, we obtain the first RMSE:

```
model_1_rmse <- RMSE(validation$rating, mu)
model_1_rmse
```

```
## [1] 1.061202
```

Here, we represent results table with the first RMSE:

```
rmse_results <- data_frame(method = "Average Movie Rating Model",
                           RMSE = model_1_rmse)
rmse_results %>% knitr::kable()
```

method	RMSE
Average Movie Rating Model	1.061202

This give us our baseline RMSE to compare with next modelling approaches.

In order to do better than simply predicting the average rating, one can incorporate some of insights gained during the exploratory data analysis.

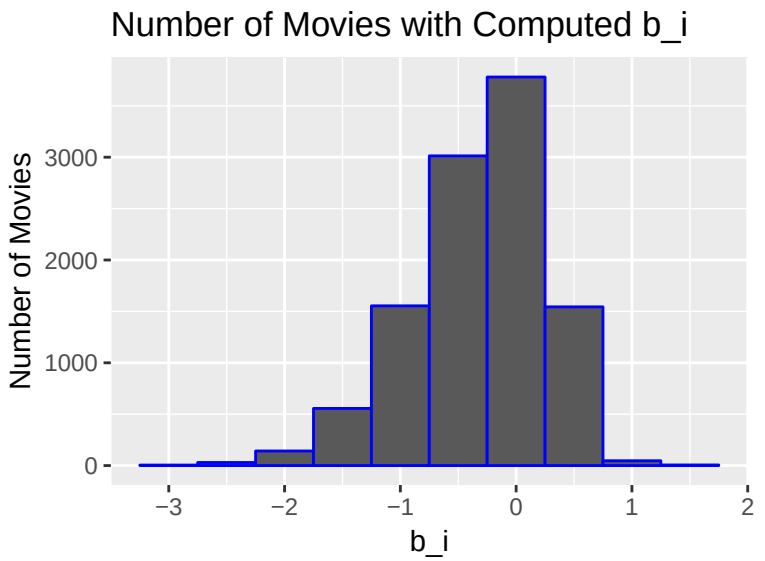
2. Movie Effect Model

To improve above model one can focus on the fact that some movies are just generally rated higher than others. Higher ratings are mostly linked to popular movies among users and the opposite is true for unpopular movies. We compute the estimated deviation of each movies' mean rating from the total mean of all movies μ. The resulting variable is called "b" (as bias) for each movie "i" b_i, that represents average ranking for movie i:

$$Y_{u,i} = \mu + b_i + \epsilon_{u,i}$$

The histogram is left skewed, implying that more movies have negative effects

```
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu))
movie_avgs %>% qplot(b_i, geom ="histogram", bins = 10,
                     data = ., color = I("blue"),
                     ylab = "Number of Movies",
                     main = "Number of Movies with Computed b_i")
```



This is called the penalty term movie effect.

Our prediction can improve once prediction is done using this model.

```
predicted_ratings <- mu +  validation %>%
  left_join(movie_avgs, by='movieId') %>%
  pull(b_i)
model_2_rmse <- RMSE(predicted_ratings, validation$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie Effect Model",
                                     RMSE = model_2_rmse ))
rmse_results %>% knitr::kable()
```

method	RMSE
Average Movie Rating Model	1.0612018
Movie Effect Model	0.9439087

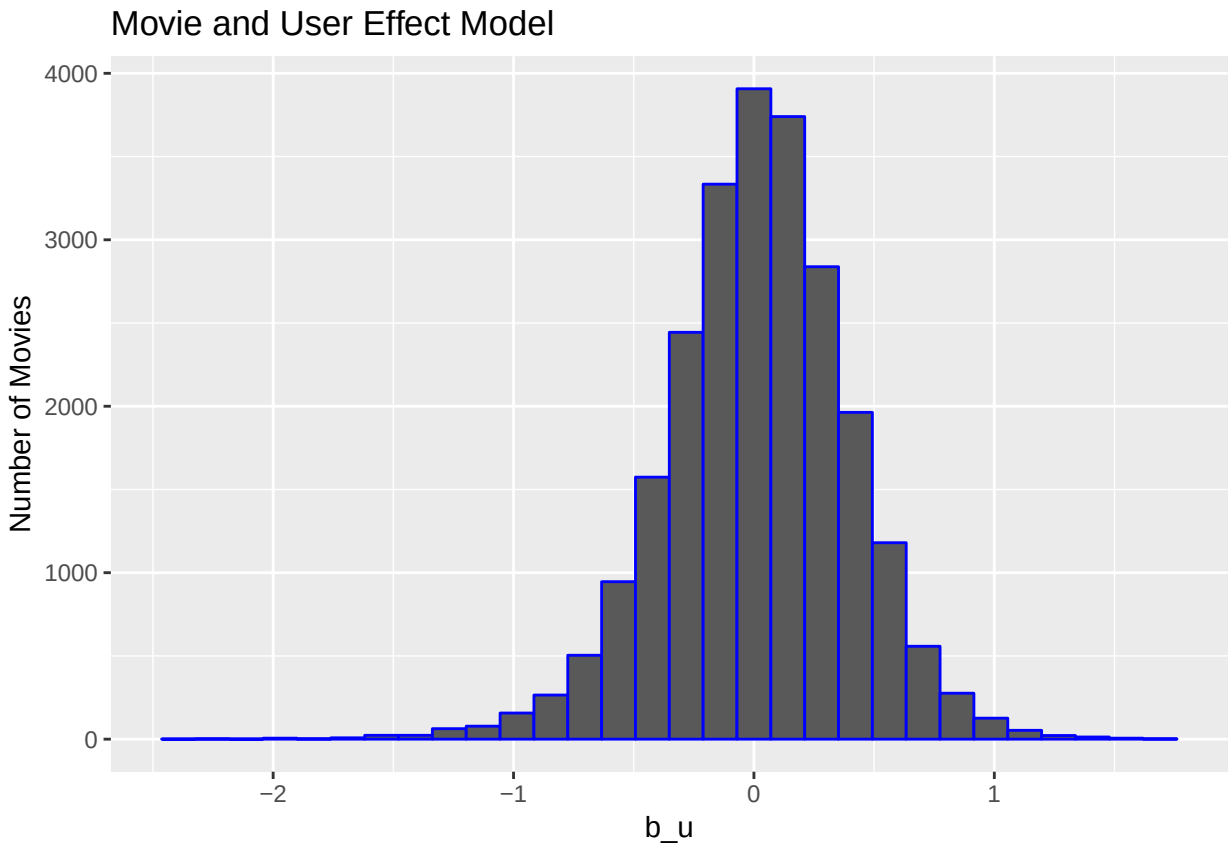
So we have predicted movie rating based on the fact that movies are rated differently by adding the computed b_i to μ. If an individual movie is on average rated worse that the average rating of all movies μ , we predict that it will rated lower that μ by b_i, the difference of the individual movie average from the total average.

We can see an improvement but this model does not consider the individual user rating effect.

3. Movie and User Effect Model

The average rating for user μ, for those that have rated over 100 movies, said penalty term user effect. In fact users affect the ratings positively or negatively.

```
user_avgs<- edx %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  filter(n() >= 100) %>%
  summarize(b_u = mean(rating - mu - b_i))
user_avgs%>% qplot(b_u, geom ="histogram",
                   bins = 30, data = ., color = I("blue"),
                   ylab = "Number of Movies",
                   main = "Movie and User Effect Model")
```



There is substantial variability across users as well: some users are very cranky and other love every movie. This implies that further improvement to our model my be:

$$Y_{u,i} = \mu + b_i + b_u + \epsilon_{u,i}$$

where b_u is a user-specific effect. If a cranky user (negative b_u rates a great movie (positive b_i), the effects counter each other and we may be able to correctly predict that this user gave this great movie a 3 rather than a 5.

An approximation can be computed by μ and b_i, and estimating b_u, as the average of

$$Y_{u,i} - \mu - b_i$$

```
user_avgs <- edx %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u = mean(rating - mu - b_i))
```

Construct predictors can improve RMSE.

```
predicted_ratings <- validation%>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  mutate(pred = mu + b_i + b_u) %>%
  pull(pred)

model_3_rmse <- RMSE(predicted_ratings, validation$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie and User Effect Model",
                                     RMSE = model_3_rmse))
rmse_results %>% knitr::kable()
```

method	RMSE
Average Movie Rating Model	1.0612018
Movie Effect Model	0.9439087
Movie and User Effect Model	0.8653488

Our rating predictions further reduced the RMSE, But still, mistakes were made on our first model (using only movies). The supposed "best " and "worst "movie were rated by few users, in most cases just one user. These movies were mostly obscure ones. This is because with a few users, more uncertainty is created. Therefore larger estimates of b_i, negative or positive, are more likely.

Until now, the computed standard error and constructed confidence intervals account for different levels of uncertainty. The concept of regularization permits to penalize large estimates that come from small sample sizes. The general idea is to add a penalty for large values of b_i to the sum of squares equation that we minimize. So having many large b_i, make it harder to minimize. Regularization is a method used to reduce the effect of overfitting.

4. Regularized Movie and User Effect Model

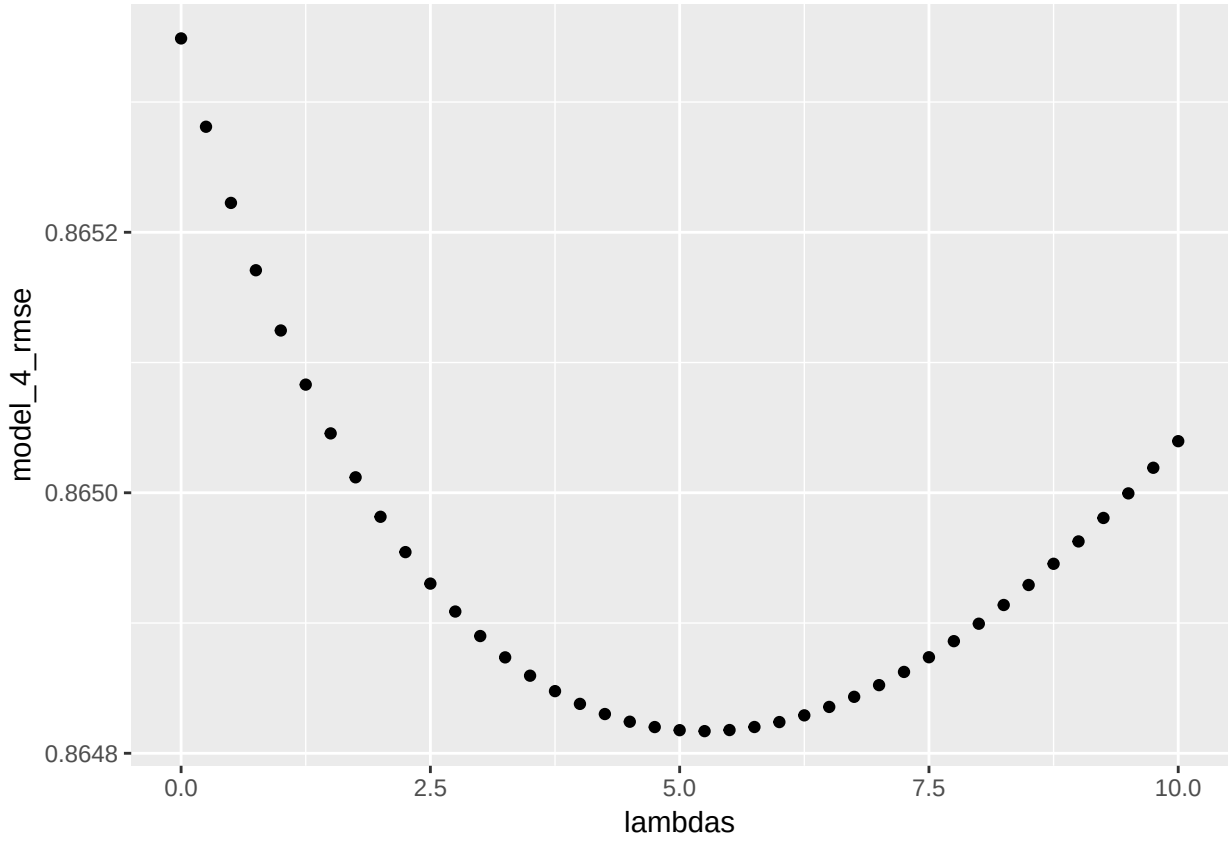
So estimates of b_i and b_u are caused by movies with very few ratings and in some users that only rated a very small number of movies. Hence this can strongly influence the prediction. The use of the regularization permits to penalize these aspects. We should find the value of lambda (that is a tuning parameter) that will minimize the RMSE. This shrinks the b_i and b_u in case of small number of ratings.

```
lambdas <- seq(0, 10, 0.25)

model_4_rmse <- sapply(lambdas, function(l){

  mu <- mean(edx$rating)

  b_i <- edx %>%
    group_by(movieId) %>%
```

```
    summarize(b_i = sum(rating - mu)/(n()+l))

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

  predicted_ratings <-
    validation %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    mutate(pred = mu + b_i + b_u) %>%
    pull(pred)

  return(RMSE(predicted_ratings, validation$rating))
})
```

We plot RMSE vs Lambdas to select the optimal lambda

```
qplot(lambdas, model_4_rmse)
```



For the full model, the optimal lambda is:

```
  lambda <- lambdas[which.min(model_4_rmse)]
lambda
```

```
## [1] 5.25
```

For the full model, the optimal lambda is: 5.25

The new results will be:

```
rmse_results <- bind_rows(rmse_results,
                          data_frame(
                            method="Regularized Movie and User Effect Model",
                                    RMSE = min(model_4_rmse)))
rmse_results %>% knitr::kable()
```

method	RMSE
Average Movie Rating Model	1.0612018
Movie Effect Model	0.9439087
Movie and User Effect Model	0.8653488
Regularized Movie and User Effect Model	0.8648170

Results

The RMSE values of all the represented models are the following:

method	RMSE
Average Movie Rating Model	1.0612018
Movie Effect Model	0.9439087
Movie and User Effect Model	0.8653488
Regularized Movie and User Effect Model	0.8648170

The lowest identified value of RMSE is 0.8648170.

Discussion

It can be confirmed that the final model for the project is the following:

$$Y_{u,i} = \mu + b_i + b_u + \epsilon_{u,i}$$

This model will work well if the average user doesn't rate a particularly good/popular movie with a large positive b_i, by disliking a particular movie.

Conclusion

A machine learning algorithm has been successfully built to predict movie ratings with MovieLens dataset. The optimal model (Regularized Model) characterised by the lowest RMSE value (0.8648170) lower than the initial evaluation criteria (0.8775) given by the goal of the present project is thus the optimal selection.