HarvardX: PH125.9x Data Science
MovieLens Rating Prediction Project

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Contents

1 1. Introduction

The main objective here is to producing product recommendations of an analytical system by applying statistical techniques. We are taking 'movielens' database to predict ratings of the movies.

The 10M version of the dataset is available in the grouplens website. Based on the different statistical models, we will build a rating predictor system.

1.0.1 Dataset

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

1.0.2 Data Loading

```
tinytex::install_tinytex()
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")
if(!require(data.table)) install.packages("data.table", repos = "http://cran.us.r-project.org")

library(readr)
movies <- read_delim("ml-10M100K/movies.dat",
                     "::", escape_double = FALSE, col_names = FALSE,
                     trim_ws = TRUE)
View(movies)
ratings <- read_delim("ml-10M100K/ratings.dat",
                     "::", escape_double = FALSE, col_names = FALSE,
                     trim_ws = TRUE)


movies <- movies %>% select(-X2,-X4)
colnames(movies) <- c("movieId", "title", "genres")

ratings <- ratings %>% select(-X2,-X4,-X6)
colnames(ratings) <- c("userId", "movieId", "rating", "timestamp")

movies <- as.data.frame(movies) %>% mutate(movieId = as.numeric(movieId)[movieId],
                                          title = as.character(title),
                                          genres = as.character(genres))

ratings <- as.data.frame(ratings) %>% mutate(userId = as.numeric(userId),
                                             movieId = as.numeric(movieId),
                                             rating = as.numeric(rating),
                                            timestamp = as.numeric(timestamp))



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

1.0.3 Libraries

The following libraries were used in this report:

```
library(ggplot2)
library(lubridate)
library(caret)
library(tidyverse)
```

1.0.4 Aim & Objectives

The provided dataset is divided into training set and validation set. We are training the first set with the machine learning algorithms and to predict movie ratings in the validation set.

Data visualization and data exploration is used to find the interesting trends and the factors affecting the users' ratings. We are creating four models based on their resulting RMSE and finalizing the optimal model to predict the movie ratings.

2 2. Methodology & Analysis

2.1 Data Pre-processing

2.1.1 Evaluation of Predicted Ratings using RMSE

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. Here, we are using the RMSE value to evaluate each model.

The function that computes the RMSE for vectors of ratings and their corresponding predictors will be the following:

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

```
# function to calculate the RMSE values
RMSE <- function(true_ratings, predicted_ratings){
  sqrt(mean((true_ratings - predicted_ratings)^2,na.rm = T))
}
```

2.1.2 Split Raw Data: Train and Test Sets

We can partition the movielens dataset into 2 sets. One set is used for building the algorithm and the second set are used for the validation of the model. The 10% of the movielens data represents the validation set.

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

```
edx <- rbind(edx, removed)
validation_CM <- validation
validation <- validation %>% select(-rating)
```

2.1.3 Modifying the Year & Genre

The title column is merged with name of the movie and the year of release. So, we are splitting the title column into name and the year column. So that we can find the dependencies between years of release and rating.

```
# Modify the year as a column in the edx & validation datasets
edx <- edx%>%separate(title,c("name", "year"), "\\s*\\((?=\\d+\\)$)|\\)$")
```

```
## Warning: Expected 2 pieces. Additional pieces discarded in 8027054 rows [1, 2,
## 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 22, ...].
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 391681 rows [20,
## 21, 39, 47, 129, 184, 189, 255, 282, 329, 338, 348, 355, 377, 381, 449, 485,
## 489, 490, 499, ...].
```

```
  validation <- validation%>%separate(title,c("name", "year"), "\\s*\\((?=\\d+\\)$)|\\)$")
```

```
## Warning: Expected 2 pieces. Additional pieces discarded in 891667 rows [1, 2, 4,
## 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 21, 22, 23, 24, ...].
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 43471 rows [3, 8,
## 16, 20, 34, 65, 106, 127, 147, 165, 190, 194, 197, 204, 240, 252, 277, 283, 292,
## 301, ...].
```

2.2 Data Visualization and Data Exploration

2.2.1 General Data Information

```
# The 1st rows of the edx are presented below:
head(edx)
```

```
##   userId movieId rating timestamp                       name year
## 1      1     122      5 838985046  Boys of St. Vincent, The 1992
## 2      1     185      5 838983525                      Nadja 1994
## 3      1     231      5 838983392      Death and the Maiden 1994
## 4      1     292      5 838983421        Once Were Warriors 1994
## 5      1     316      5 838983392 Secret of Roan Inish, The 1994
## 6      1     329      5 838983392         To Live (Huozhe) 1994
##                           genres
## 1                          Drama
## 2                          Drama
## 3                 Drama|Thriller
```

```
## 4                    Crime|Drama
## 5 Children|Drama|Fantasy|Mystery
## 6                          Drama
```

```
# Summary Statistics of edx
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
##      name               year              genres
##  Length:9000061     Length:9000061     Length:9000061
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
```

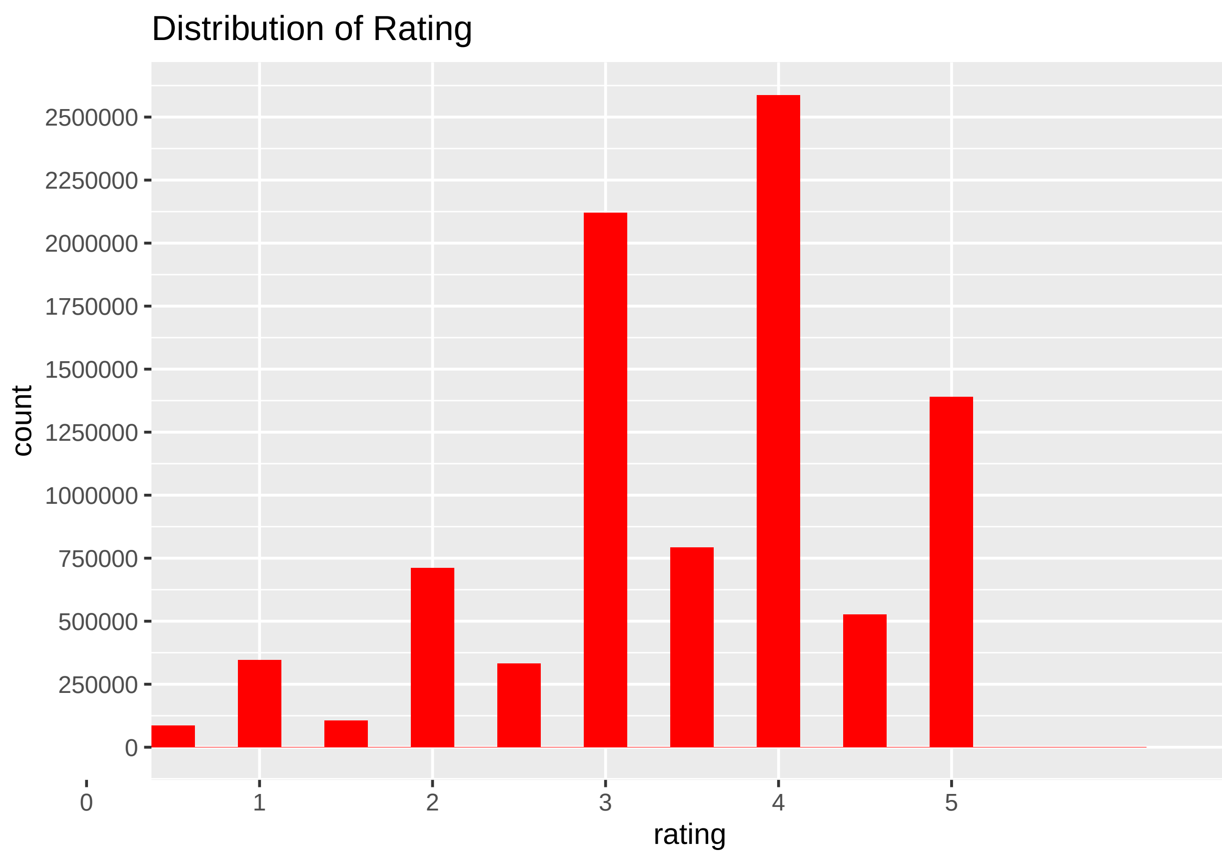
```
# Number of unique movies and users in the edx dataset
edx %>% summarize(n_users = n_distinct(userId), n_movies = n_distinct(movieId))
```

```
##   n_users n_movies
## 1   69878    10677
```

2.2.2 Distribution of Ratings

Most common ratings are 3 and 4 compared to other ratings. Then half star ratings are less popular to whole star ratings. The preference of the users is with the higher ratings than lower ratings.

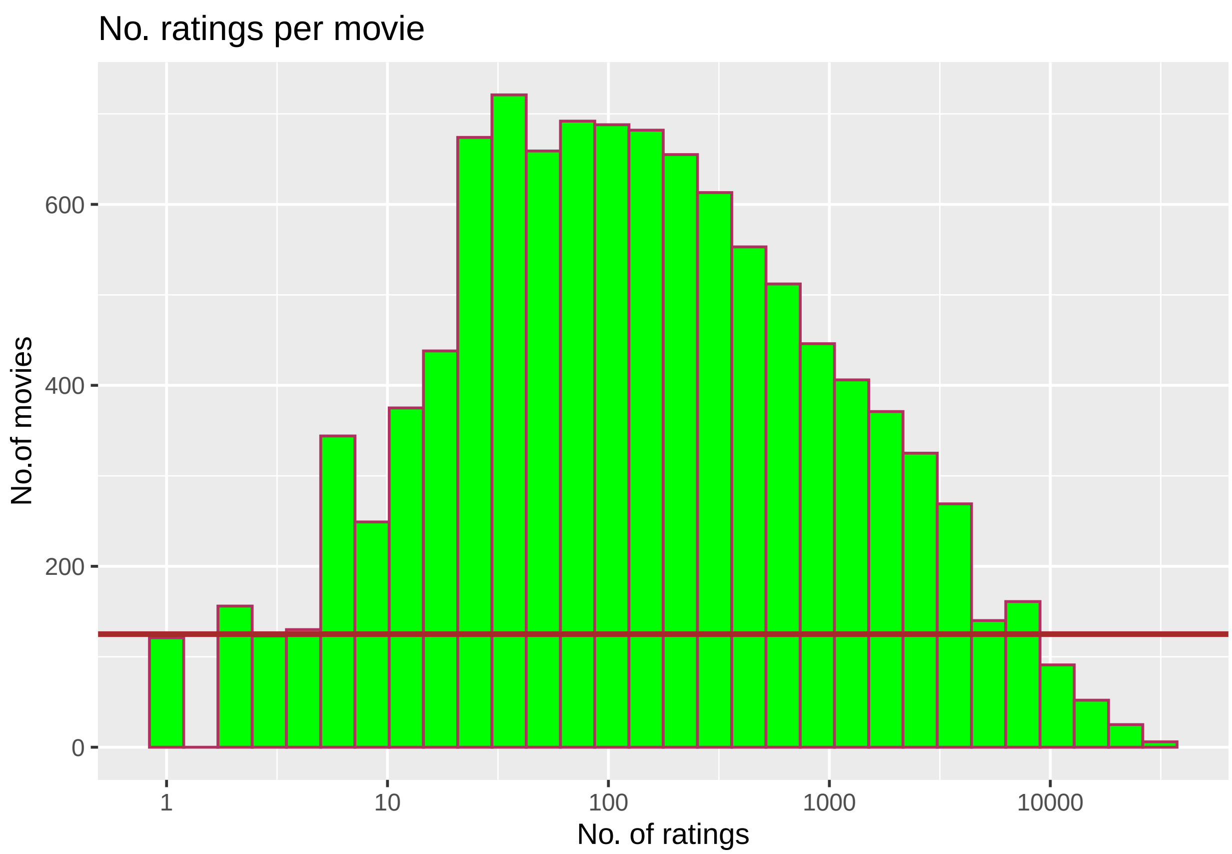
```
 edx %>%
    ggplot(aes(rating)) + geom_histogram(binwidth=0.25, fill = "red") +
    scale_x_discrete(limits = c(seq(0,5,1))) +
    scale_y_continuous(breaks = c(seq(0, 3000000, 250000))) +
    ggtitle("Distribution of Rating")
```



2.2.3 Ratings per movie

The majority of the movies have been rated between 50 and 1000 times. Another interesting fact shows that around 125 movies have been rated only once. These scenarios pushed us to add a penalty term in the model preparation.

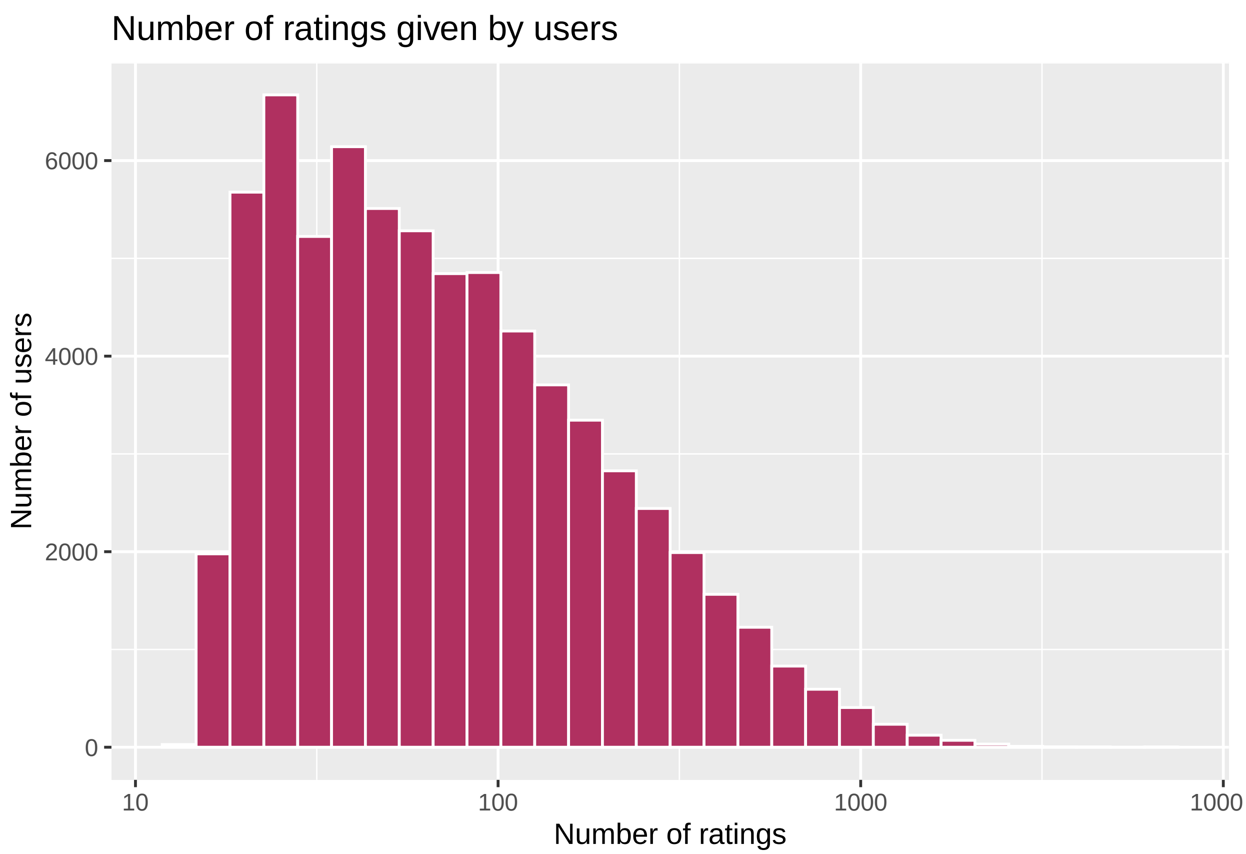
```
edx %>%
    count(movieId) %>%
    ggplot(aes(n)) +
    geom_histogram(bins = 30, color = "maroon", fill = "green") +
    scale_x_log10() +
  geom_hline(yintercept=125, color = "brown",size=1) +
    xlab("No. of ratings") +
    ylab("No.of movies") +
    ggtitle("No. ratings per movie")
```



2.2.4 Number of ratings by Number of Users

The majority people have rated below 100 movies and above 30 movies. So a penalty term would be added for this.

```
edx %>%
    count(userId) %>%
    ggplot(aes(n)) +
    geom_histogram(bins = 30, color = "white", fill = "maroon") +
    scale_x_log10() +
    xlab("Number of ratings") +
    ylab("Number of users") +
    ggtitle("Number of ratings given by users")
```



Total movie ratings per genre

This shows the genre details of the movielens dataset.

```r
edx%>%
    group_by(genres) %>%
    summarize(count = n()) %>%
    arrange(desc(count))
```

```
## # A tibble: 629 x 2
##    genres                 count
##    <chr>                  <int>
##  1 Drama                1370890
##  2 <NA>                  965190
##  3 Comedy                867118
##  4 Comedy|Drama          397149
##  5 Comedy|Romance        347771
##  6 Drama|Romance         306098
##  7 Comedy|Drama|Romance  208686
##  8 Horror                182946
##  9 Drama|Thriller        182596
## 10 Documentary           167660
## # ... with 619 more rows
```

2.3 Data Analysis and modelling

```
#Initiate RMSE results to compare various models
rmse_results <- data_frame()
```

```
## Warning: `data_frame()` is deprecated, use `tibble()`.
## This warning is displayed once per session.
```

2.3.1 Sample estimate- mean

The initial step is to compute the dataset's mean rating.

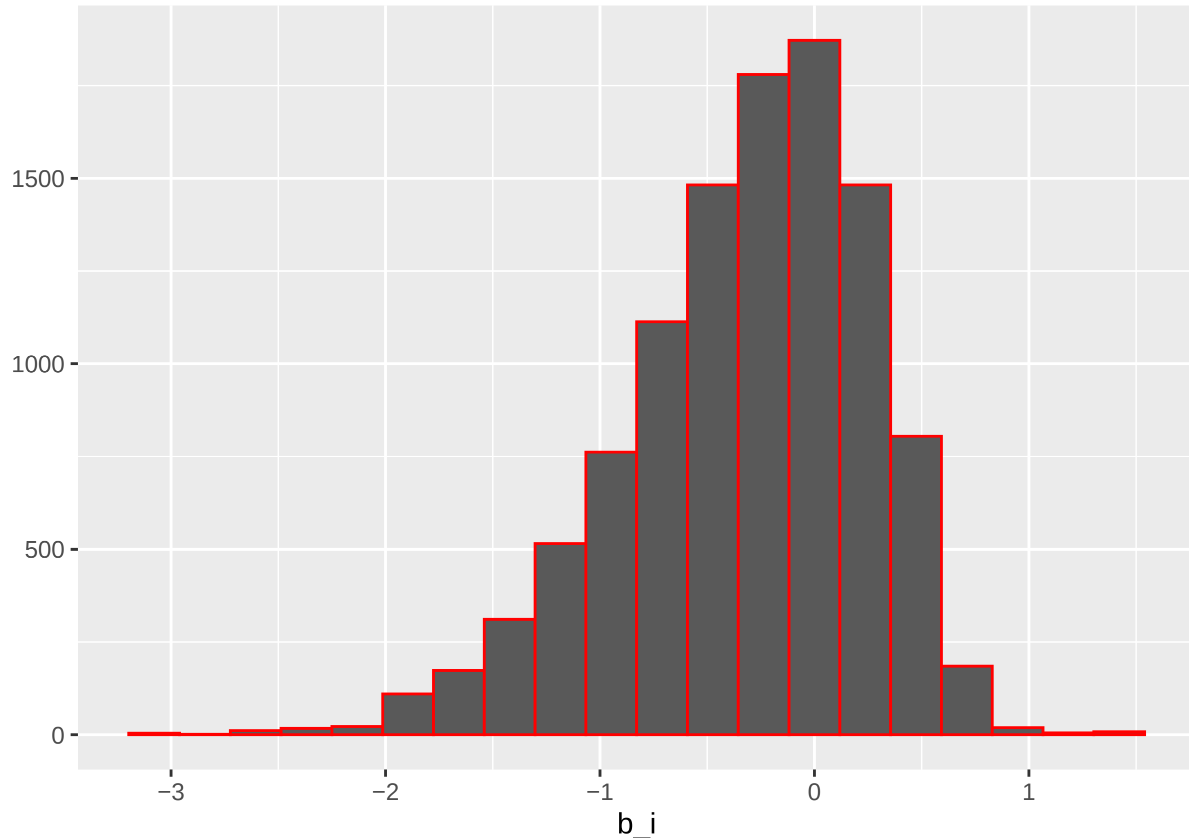
```
mu <- mean(edx$rating)
mu
```

```
## [1] 3.512464
```

2.3.2 Movie Effect - Penalty

Popular movies have higher rating mostly and unpopular movies have low ratings. The histogram is left skewed and it shows that more movies have negative effects.

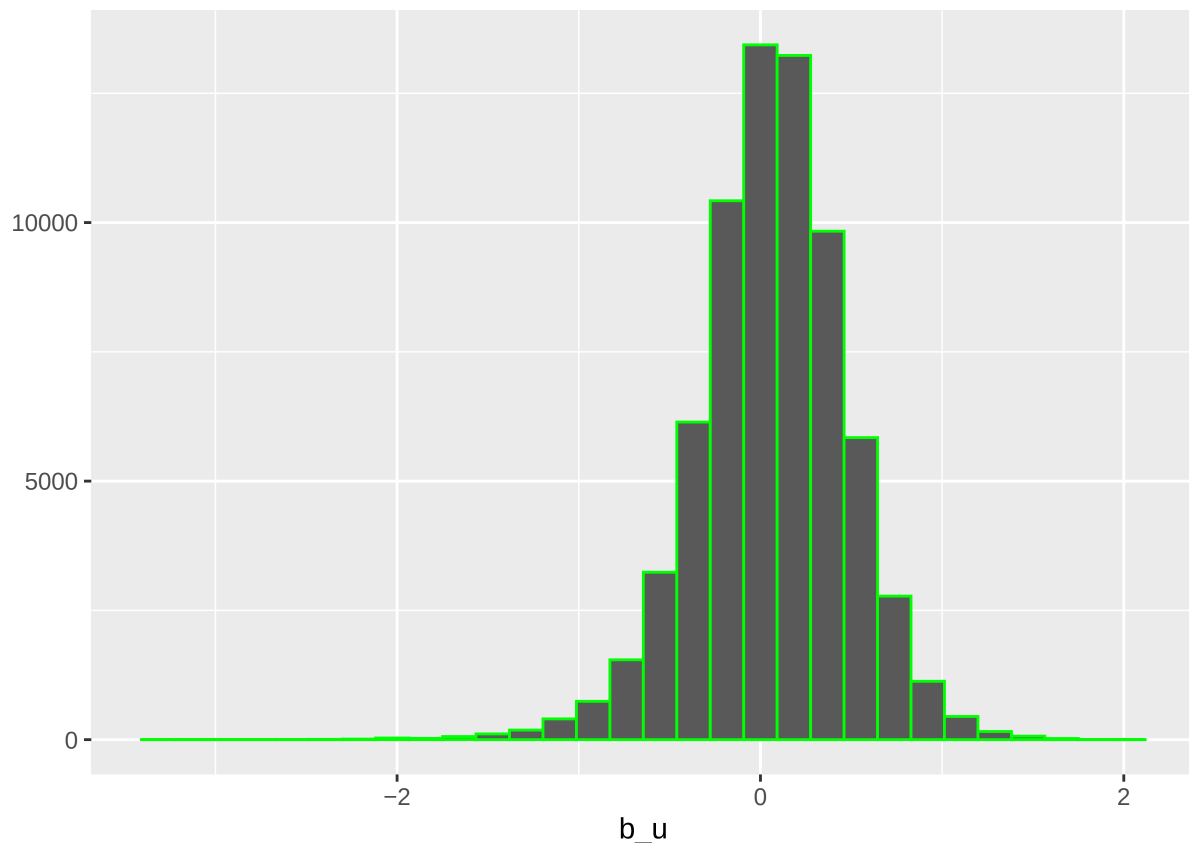
```
movie_av <- edx %>%
    group_by(movieId) %>%
    summarize(b_i = mean(rating - mu))

movie_av %>% qplot(b_i, geom ="histogram", bins = 20, data = ., color = I("red"))
```



2.3.3 User Effect - Penalty

Some users can also affect the ratings either positively(by giving higher ratings) or negatively.

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

user_av %>% qplot(b_u, geom ="histogram", bins = 30, data = ., color = I("green"))
```



Model Creation #### Model Validation

The quality of the model will be assessed by the RMSE (the lower the better).

2.3.4 Naive Model : just the mean

This model uses the sample mean represents the initial simplest model. This implies that prediction is the sample average. The resulting RMSE is quite high with this model.

```
# Naive Model -- mean only
naive_rmse <- RMSE(validation_CM$rating,mu)
## Test results based on simple prediction
naive_rmse
```

```
## [1] 1.060651
```

```
## Check results
rmse_results <- data_frame(method = "Using mean only", RMSE = naive_rmse)
rmse_results
```

```
## # A tibble: 1 x 2
##   method           RMSE
##   <chr>           <dbl>
## 1 Using mean only  1.06
```

```
## Save prediction in data frame
```

2.3.5 Movie Effect Model

The RMSE improvisation can be done by adding the movie effect.

```
predrat_movie_norm <- validation %>%
    left_join(movie_av, by='movieId') %>%
    mutate(pred = mu + b_i)

model_1_rmse <- RMSE(validation_CM$rating,predrat_movie_norm$pred)

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

method	RMSE
Using mean only	1.0606506
Movie Effect Model	0.9437046

```
rmse_results
```

```
## # A tibble: 2 x 2
##   method              RMSE
##   <chr>              <dbl>
## 1 Using mean only    1.06
## 2 Movie Effect Model 0.944
```

2.3.6 Movie and User Effect Model

Next improvisation is achieved by adding the user effect.

```
# Use test set,join movie averages & user averages
# Prediction equals the mean with user effect b_u & movie effect b_i
  predrat_user_norm <- validation %>%
    left_join(movie_av, by='movieId') %>%
    left_join(user_av, by='userId') %>%
    mutate(pred = mu + b_i + b_u)

  # test and save rmse results

  model_2_rmse <- RMSE(validation_CM$rating,predrat_user_norm$pred)
  rmse_results <- bind_rows(rmse_results,
                            data_frame(method="Movie and User Effect Model",
                                       RMSE = model_2_rmse ))
  rmse_results %>% knitr::kable()
```

method	RMSE
Using mean only	1.0606506
Movie Effect Model	0.9437046
Movie and User Effect Model	0.8655329

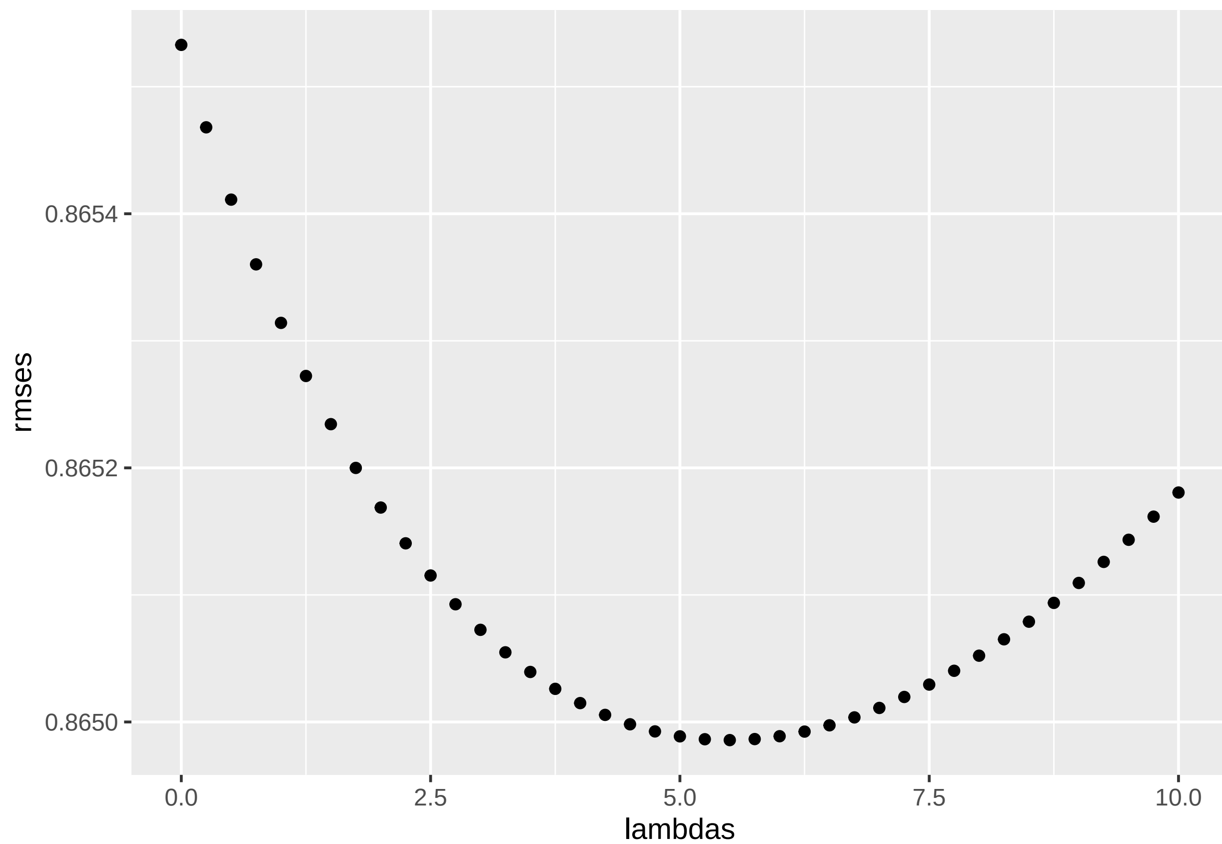
```
rmse_results
```

```
## # A tibble: 3 x 2
##   method                       RMSE
##   <chr>                       <dbl>
## 1 Using mean only             1.06
## 2 Movie Effect Model          0.944
## 3 Movie and User Effect Model 0.866
```

2.3.7 Regularized Movie and User Effect Model

This model adds the concept of regularization to account for the effect of low ratings' numbers for movies and users. This regularization used to reduce the effect of overfitting.

```
# lambda is a tuning parameter
# Use cross-validation to choose it.
lambdas <- seq(0, 10, 0.25)
  # For each lambda,find b_i & b_u, followed by rating prediction & testing
  # note:the below code could take some time
  rmses <- 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))

    predrat <-
      validation %>%
      left_join(b_i, by = "movieId") %>%
      left_join(b_u, by = "userId") %>%
      mutate(pred = mu + b_i + b_u) %>%
      .$pred
      return(RMSE(predrat,validation_CM$rating))

  })


  # Plot rmses vs lambdas to select the optimal lambda
  qplot(lambdas, rmses)
```




```
# The optimal lambda
lambda <- lambdas[which.min(rmses)]
#lambda <- 5.25

# Compute regularized estimates of b_i using lambda
movie_av_reg <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mu)/(n()+lambda), n_i = n())

# Compute regularized estimates of b_u using lambda

user_av_reg <- edx %>%
  left_join(movie_av_reg, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u = sum(rating - mu - b_i)/(n()+lambda), n_u = n())

# Predict ratings

predrat_reg <- validation %>%
  left_join(movie_av_reg, by='movieId') %>%
  left_join(user_av_reg, by='userId') %>%
  mutate(pred = mu + b_i + b_u) %>%
  .$pred


# Test and save results
```

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

method	RMSE
Using mean only	1.0606506
Movie Effect Model	0.9437046
Movie and User Effect Model	0.8655329
Regularized Movie and User Effect Model	0.8649857

```r
rmse_results
```

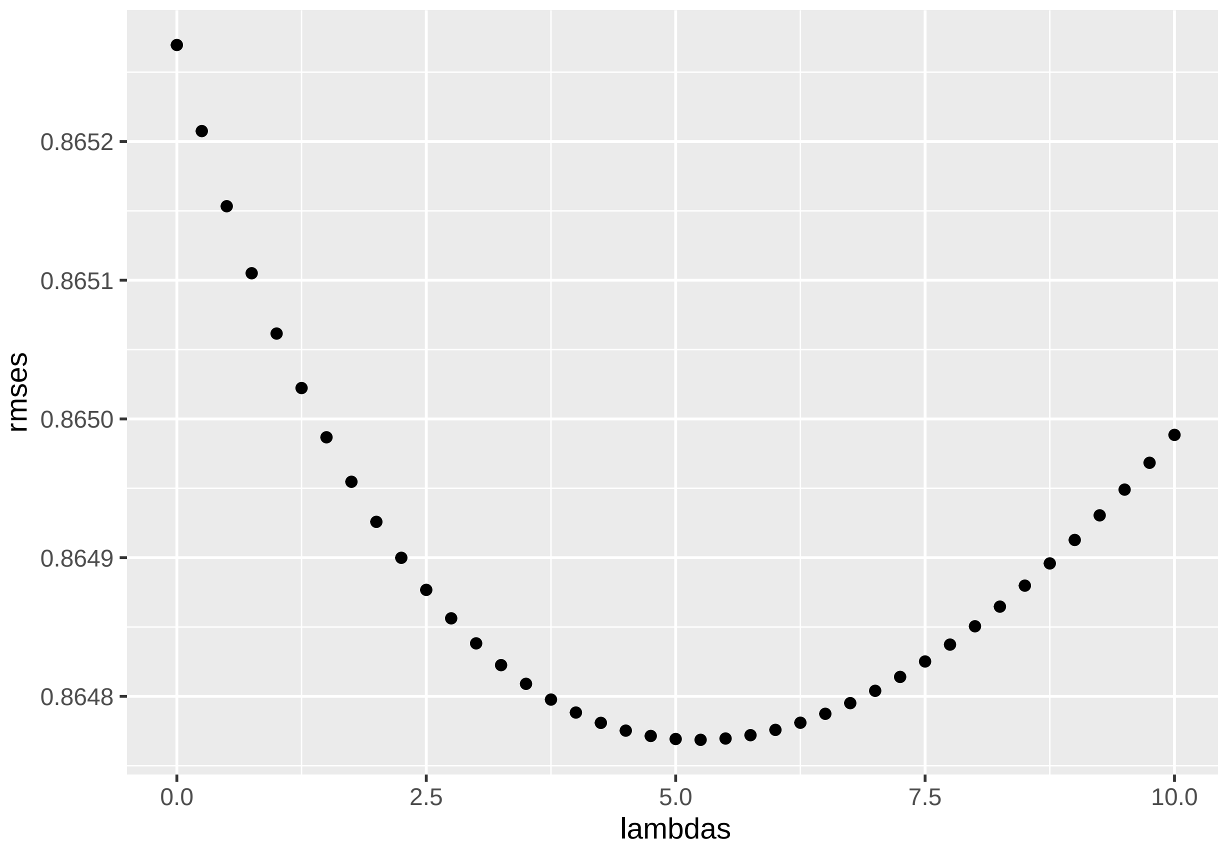
```
## # A tibble: 4 x 2
##   method                                   RMSE
##   <chr>                                   <dbl>
## 1 Using mean only                         1.06
## 2 Movie Effect Model                      0.944
## 3 Movie and User Effect Model             0.866
## 4 Regularized Movie and User Effect Model 0.865
```

2.3.8 Regularized Movie, User and year Effect Model

This model adds the concept of regularization to account for the effect of low ratings' numbers for movies and users with year. This regularization used to reduce the effect of overfitting compared to earlier model.

```r
# lambda is a tuning parameter
# Use cross-validation to choose it.
lambdas <- seq(0, 10, 0.25)
  # For each lambda,find b_i & b_u, followed by rating prediction & testing
  # note:the below code could take some time
  rmses <- sapply(lambdas, function(l){

    mu <- mean(edx$rating)

    b_i1 <- edx %>%
      group_by(movieId) %>%
      summarize(b_i1 = sum(rating - mu)/(n()+l))

    b_u1 <- edx %>%
      left_join(b_i1, by="movieId") %>%
      group_by(userId) %>%
      summarize(b_u1 = sum(rating - b_i1 - mu)/(n()+l))


    b_y1 <- edx %>%
      left_join(b_i1, by="movieId") %>%
      left_join(b_u1, by="userId") %>%
      group_by(year) %>%
```

```
    summarize(b_y1 = sum(rating - b_u1 - b_i1 - mu)/(n()+l))


  predrat1 <-
    validation %>%
    left_join(b_i1, by = "movieId") %>%
    left_join(b_u1, by = "userId") %>%
    left_join(b_y1, by = "year") %>%
    mutate(pred = mu + b_i1 + b_u1 + b_y1) %>%
    pull(pred)

    return(RMSE(predrat1, validation_CM$rating))
})


# Plot rmses vs lambdas to select the optimal lambda
qplot(lambdas, rmses)
```




```
# The optimal lambda
lambda <- lambdas[which.min(rmses)]
#lambda <- 5.25

# Compute regularized estimates of b_i using lambda
movie_av_reg1 <- edx %>%
  group_by(movieId) %>%
```

```r
  summarize(b_i1 = sum(rating - mu)/(n()+lambda), n_i1 = n())

# Compute regularized estimates of b_u using lambda

user_av_reg1 <- edx %>%
  left_join(movie_av_reg1, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u1 = sum(rating - mu - b_i1)/(n()+lambda), n_u1 = n())

# Compute regularized estimates of b_y using lambda

year_av_reg1 <- edx %>%
  left_join(movie_av_reg1, by='movieId') %>%
  left_join(user_av_reg1, by='userId') %>%
  group_by(year) %>%
  summarize(b_y1 = sum(rating - mu - b_i1 - b_u1)/(n()+lambda), n_y1 = n())

# Predict ratings

predrat_reg1 <- validation %>%
  left_join(movie_av_reg1, by='movieId') %>%
  left_join(user_av_reg1, by='userId') %>%
  left_join(year_av_reg1, by = 'year') %>%
  mutate(pred = mu + b_i1 + b_u1 + b_y1) %>%
  .$pred


# Test and save results

model_4_rmse <- RMSE(validation_CM$rating,predrat_reg1)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Regularized Movie User and Year Effect Model",
                                     RMSE = model_4_rmse ))
rmse_results %>% knitr::kable()
```

method	RMSE
Using mean only	1.0606506
Movie Effect Model	0.9437046
Movie and User Effect Model	0.8655329
Regularized Movie and User Effect Model	0.8649857
Regularized Movie User and Year Effect Model	0.8647687

```r
rmse_results
```

```
## # A tibble: 5 x 2
##   method                                   RMSE
##   <chr>                                   <dbl>
## 1 Using mean only                         1.06
## 2 Movie Effect Model                      0.944
## 3 Movie and User Effect Model             0.866
## 4 Regularized Movie and User Effect Model 0.865
```

```
## 5 Regularized Movie User and Year Effect Model 0.865
```

3 4. Conclusion

The regularized model including the effect of movie, user, genre and year is characterized by the lowest RMSE value (0.8623650) and is hence the optimal model to use for the present project.

Further improvement to this model could be achieved by adding the effect of gender and age on the movies' genre preference combined with the user's profession effect on ratings (different professions do

4 Appendix - Enviroment

```r
print("Operating System:")
```

```
## [1] "Operating System:"
```

```r
version
```

```
##                _
## platform       x86_64-w64-mingw32
## arch           x86_64
## os             mingw32
## system         x86_64, mingw32
## status
## major          3
## minor          6.3
## year           2020
## month          02
## day            29
## svn rev        77875
## language       R
## version.string R version 3.6.3 (2020-02-29)
## nickname       Holding the Windsock
```