Capstone MovieLens Project

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1.Introduction

The MovieLens project is using the MovieLens 10M dataset to predict movie ratings in the validation set which containing part of MovieLens data. The main purpose of this project about the method to create and test the algorithm and predict movie ratings using the validation set by RMSE.

The key steps performed as shown below:

1.1 MovieLens 10M dataset.

```
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")
```

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

ratings <- fread(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")
```

1.2 Validation set will be 10% of 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,]
```

1.3 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")
```

1.4 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)
```

2.Data exploration

2.1 Find overall data in the dataset.

```
head(edx)
```

```
##    userId movieId rating timestamp                         title
## 1:      1     122      5 838985046              Boomerang (1992)
## 2:      1     185      5 838983525               Net, The (1995)
## 3:      1     231      5 838983392          Dumb & Dumber (1994)
## 4:      1     292      5 838983421               Outbreak (1995)
## 5:      1     316      5 838983392               Stargate (1994)
## 6:      1     329      5 838983392 Star Trek: Generations (1994)
##                            genres
## 1:                Comedy|Romance
## 2:         Action|Crime|Thriller
## 3:                        Comedy
## 4:  Action|Drama|Sci-Fi|Thriller
## 5:       Action|Adventure|Sci-Fi
## 6: Action|Adventure|Drama|Sci-Fi
```

```
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:9000061     Length:9000061
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##
```

2.2 In the edx set, there are 9000061 rows and 6 columns.

```
dim(edx)
```

```
## [1] 9000061       6
```

2.3 No movies have a rating of 0 and 2121638 movies have a rating of 3 can be found.

```
edx %>% filter(rating == 0) %>% tally()
```

```
##   n
## 1 0
```

```
edx %>% filter(rating == 3) %>% tally()
```

```
##         n
## 1 2121638
```

2.4 The edx dataset is including 10677 movies and 68978 users.

```
data.frame(Movies= n_distinct(edx$movieId), Users=n_distinct(edx$userId))
```

```
##   Movies Users
```

```
## 1  10677 69878
```

2.5 The number of movie rating are in each of the following genres in the edx dataset.

```
edx %>% separate_rows(genres, sep = "\\|") %>%
   group_by(genres) %>% summarize(count = n()) %>% arrange(desc(count))
```

```
## # A tibble: 20 x 2
##    genres               count
##    <chr>                <int>
##  1 Drama               3909401
##  2 Comedy              3541284
##  3 Action              2560649
##  4 Thriller            2325349
##  5 Adventure           1908692
##  6 Romance             1712232
##  7 Sci-Fi              1341750
##  8 Crime               1326917
##  9 Fantasy              925624
## 10 Children             737851
## 11 Horror               691407
## 12 Mystery              567865
## 13 War                  511330
## 14 Animation            467220
## 15 Musical              432960
## 16 Western              189234
## 17 Film-Noir            118394
## 18 Documentary           93252
## 19 IMAX                   8190
## 20 (no genres listed)        6
```

2.6 It shows the top ten movies of rating and the movie "Pulp Fiction" has the greatest number of ratings.

```
edx %>% group_by(movieId, title) %>% summarize(count = n()) %>% arrange(desc(count))
```

```
## # A tibble: 10,677 x 3
## # Groups:   movieId [10,677]
##    movieId title                                                     count
##      <dbl> <chr>                                                     <int>
##  1     296 Pulp Fiction (1994)                                       31336
##  2     356 Forrest Gump (1994)                                       31076
##  3     593 Silence of the Lambs, The (1991)                          30280
##  4     480 Jurassic Park (1993)                                      29291
##  5     318 Shawshank Redemption, The (1994)                          27988
##  6     110 Braveheart (1995)                                         26258
##  7     589 Terminator 2: Judgment Day (1991)                         26115
##  8     457 Fugitive, The (1993)                                      26050
##  9     260 Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977) 25809
## 10     592 Batman (1989)                                             24343
## # ... with 10,667 more rows
```

2.7 The top five ratings are shown as below, which rating of 4 is the most and 2 is the least given ratings.

```
edx %>% group_by(rating) %>% summarize(count = n()) %>% top_n(5) %>% arrange(desc(count))
```

```
## # A tibble: 5 x 2
##   rating   count
##    <dbl>   <int>
```

```
## 1    4   2588021
## 2    3   2121638
## 3    5   1390541
## 4    3.5  792037
## 5    2    710998
```

2.8 The following code is shown that half star ratings are less common than whole star ratings.

```
edx %>% group_by(rating) %>% summarize(count = n())
```

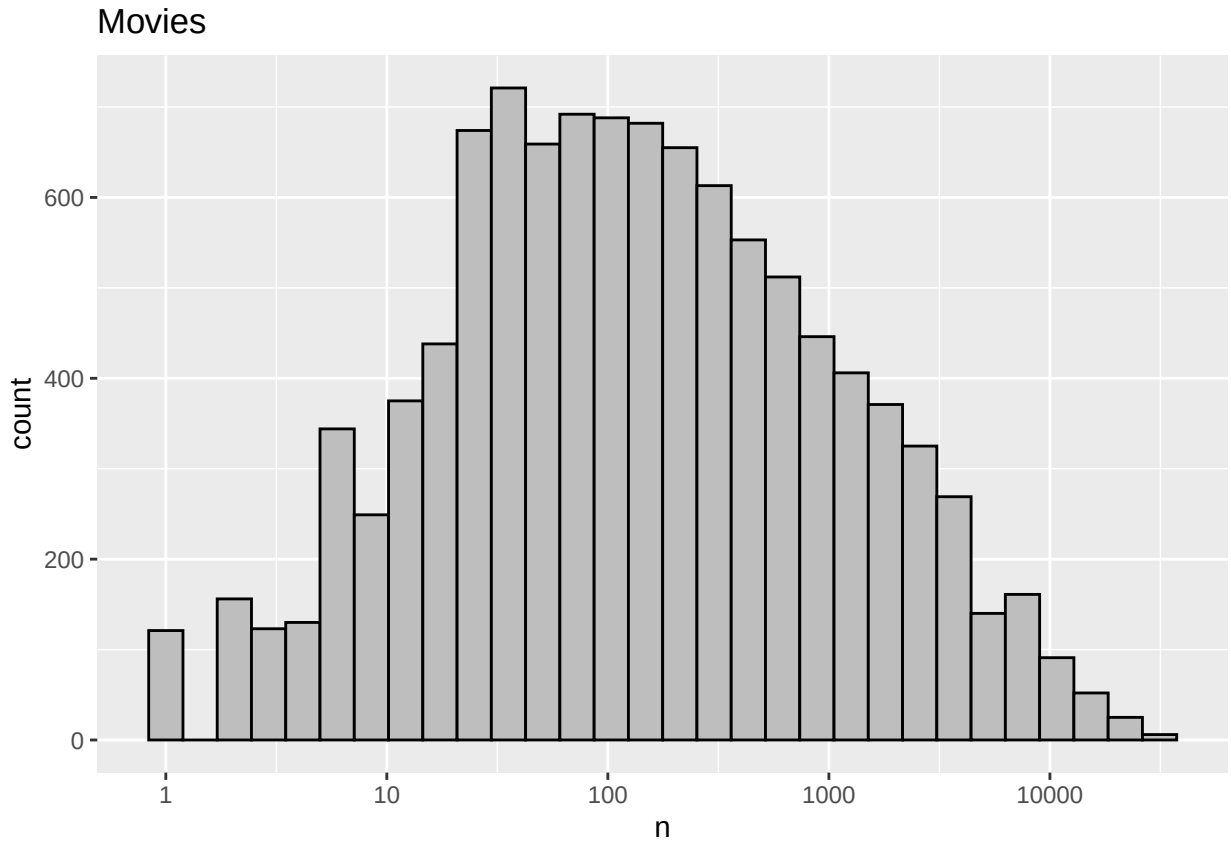
```
## # A tibble: 10 x 2
##    rating   count
##     <dbl>   <int>
##  1    0.5   85420
##  2    1    345935
##  3    1.5  106379
##  4    2    710998
##  5    2.5  332783
##  6    3   2121638
##  7    3.5  792037
##  8    4   2588021
##  9    4.5  526309
## 10    5   1390541
```

The basic infomation is shown above and we start to analysis the information in the following section.

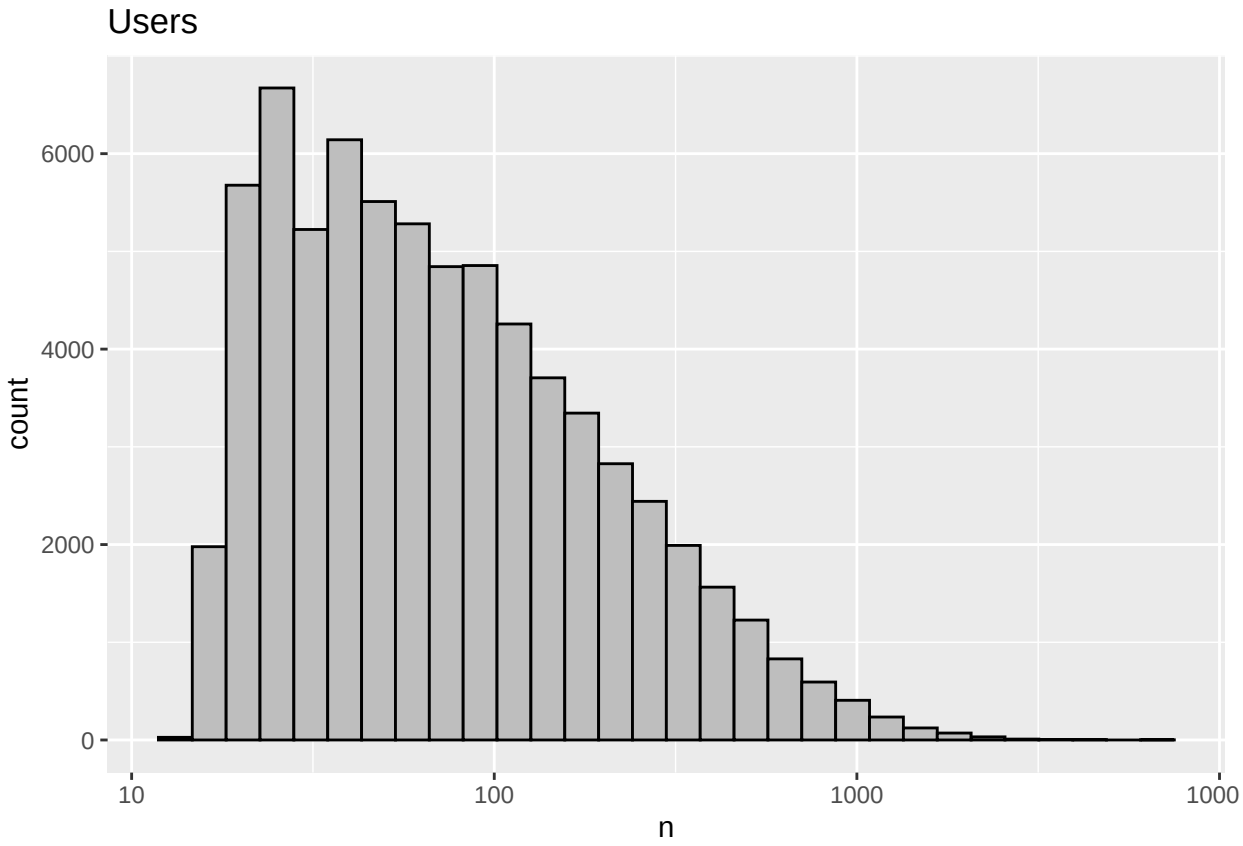
3.Analysis and Result

3.1 The general properties of the Movie and User data.

```
edx %>% count(movieId) %>%
  ggplot(aes(n)) + geom_histogram(fill = "grey", color = "black", bins = 30) +
  scale_x_log10() + xlab("n") + ylab("count") +
  ggtitle("Movies")
```




```
edx %>% count(userId) %>%
  ggplot(aes(n)) + geom_histogram(fill = "grey", color = "black", bins = 30) +
  scale_x_log10() + xlab("n") + ylab("count") +
  ggtitle("Users")
```



3.2 Computing the RMSE for vectors of ratings and their corresponding predictors.

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

3.3 Creating the average of all ratings model.

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

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

3.4 Predicting all unknown ratings with mu we obtain the following RMSE

```
naive_rmse <- RMSE(validation$rating, mu_hat)
naive_rmse
```

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

3.5 Creating a results table with this naive approach

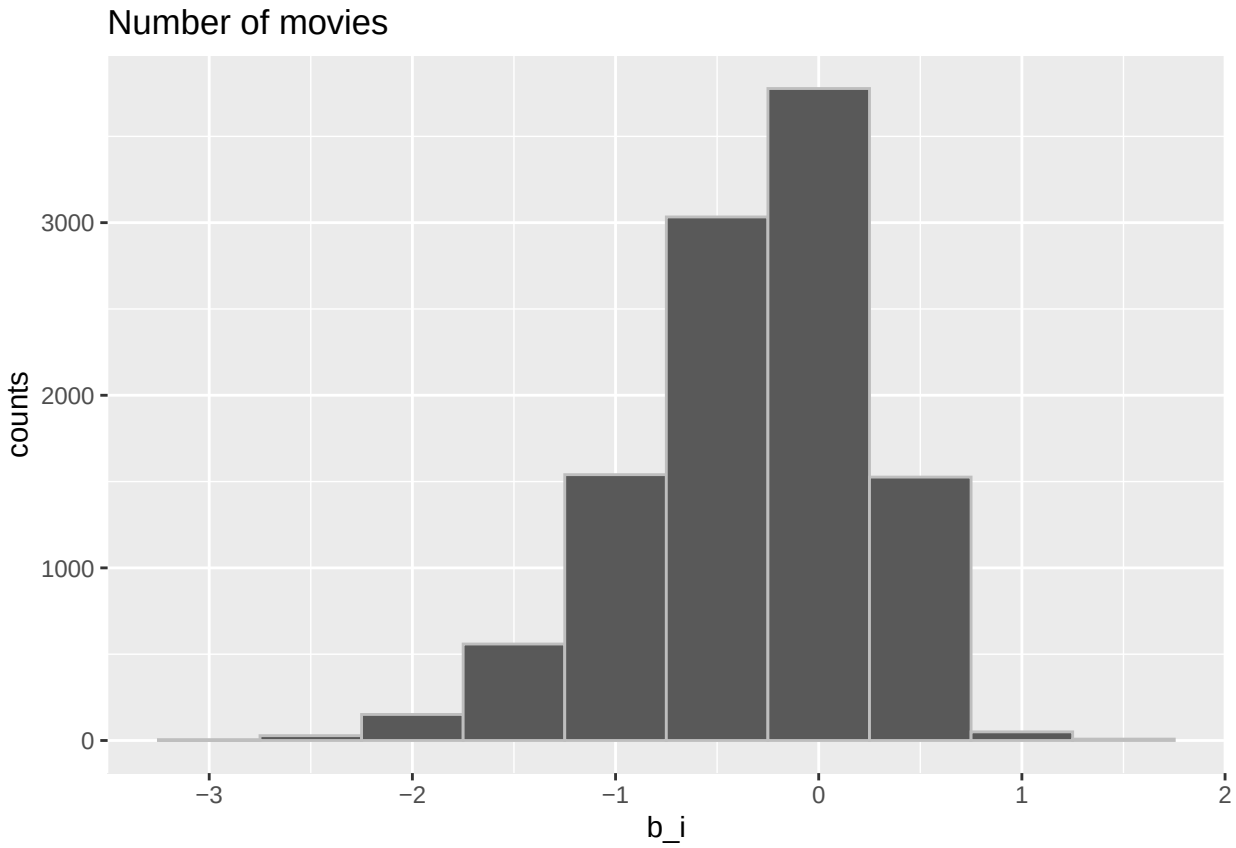
```
rmse_results <- tibble(method = "Just the average", RMSE = naive_rmse)
rmse_results
```

```
## # A tibble: 1 x 2
##   method            RMSE
##   <chr>            <dbl>
## 1 Just the average  1.06
```

The result of this model of the average rating is 3.51, and RMSE is 1.06. So we can definitely do better!

3.6 Now we create movie effects model.

```
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu_hat))

movie_avgs %>% qplot(b_i, geom ="histogram", bins = 10, data = ., color = I("grey"),
                     ylab = "counts", main = "Number of movies")
```



3.7 The predict result of movie effects model.

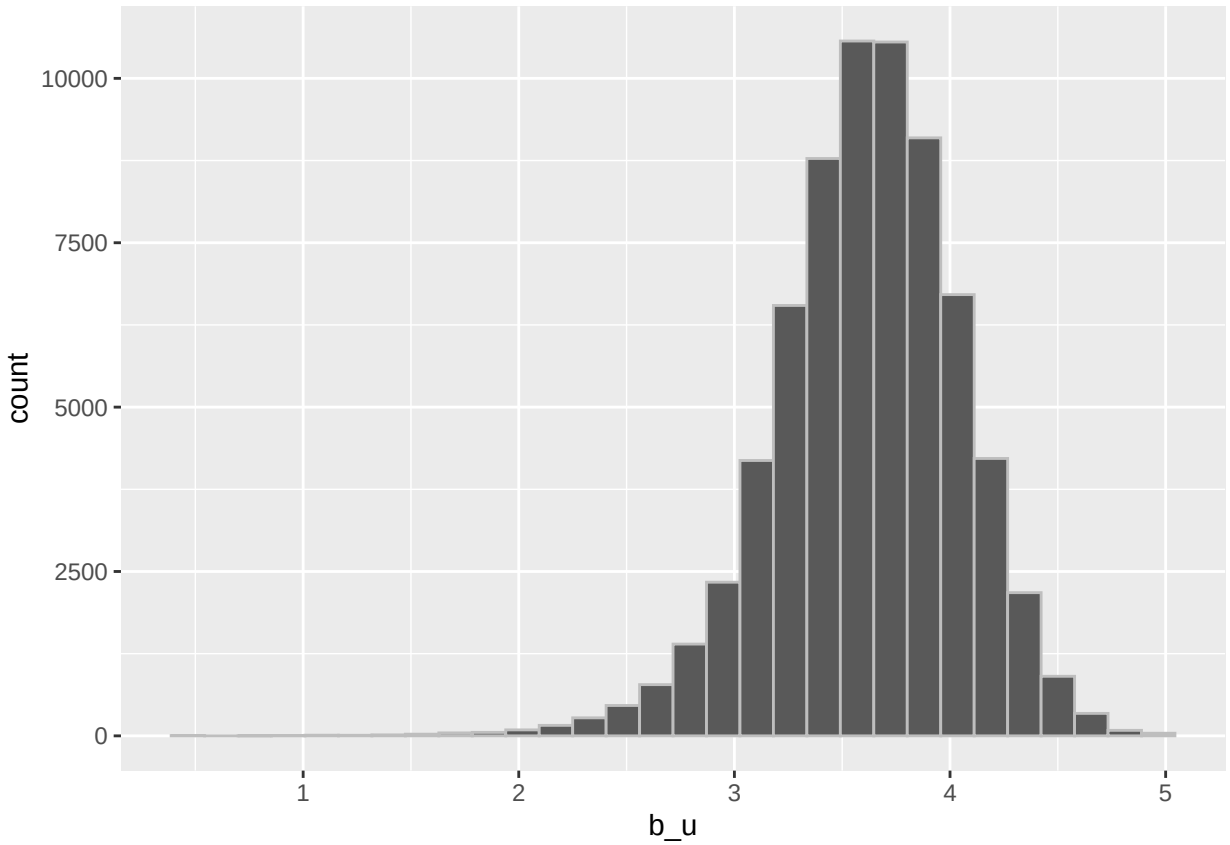
```
predicted_ratings <- mu_hat + validation %>%
   left_join(movie_avgs, by='movieId') %>% pull(b_i)

RMSE(predicted_ratings, validation$rating)
```

```
## [1] 0.9437046
```

The predict result is 0.94 and we believe that we can do much metter.

3.8 Creating user effect model and computing the average rating for user.

```
edx %>% group_by(userId) %>%
   summarize(b_u = mean(rating)) %>%
   filter(n()>=100) %>% ggplot(aes(b_u)) +
   geom_histogram(bins = 30, color = "grey")
```



3.9 Computing an approximation by computing mu and bi and estimating bu as the average of yu,i - mu - bi:

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

3.10 Constructing predictors and see how much the RMSE improves.

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

RMSE(predicted_ratings, validation$rating)
```

```
## [1] 0.8655329
```

The result of RMSE is 0.865.

Conclusion

As the result, the algorithm achieved a final RMSE value, which is fulfilled the requirement. It is a challenging project and learn a lot about the machine learning and build up the model to analysis the result.