MovieLens Report

Dhuha Alghanmi

2/17/2019

Introduction

A recommender system or a recommendation system is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user would give to an item. Recommendation systems use ratings that users have given items to make specific recommendations. Companies that sell many products to many customers and permit these customers to rate their products, use customers rating to predict their preferences or rating for another item. Netflix uses a recommendation system to predict if user rating for specific movies. motivated by some of the approaches taken by the winners of the Netflix challenges, On October 2006, Netflix offered a challenge to the data science community: improve our recommendation algorithm by 10% and win a million dollars. In September 2009, the winners were announced. You can read a good summary of how the winning algorithm was put together here and a more detailed explanation here. We will now show you some of the data analysis strategies used by the winning team.

This assignment is to accomplish a similar goal which is to build a recommendation system that recommends movies based on a rating scale.

Data set

For this project the MovieLens Data set collected by GroupLens Research and can be found in MovieLens web site (http://movielens.org).

Data Loading

The data set is loaded using the code provided by course instucture in this link https://bit.ly/2Ng6tVW which split the data into edx set and 10% validation set. the edx set will be split into training and test set,and validation set will be used to final evaluation.

```
#############################################################
# Create edx set, validation set, and submission file
#############################################################

# Note: this process could take a couple of minutes
```

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

## Loading required package: tidyverse

## -- Attaching packages ---------------------------------------
tidyverse 1.2.1 --

## v ggplot2 3.1.0     v purrr   0.2.5
## v tibble  1.4.2     v dplyr   0.7.8
## v tidyr   0.8.2     v stringr 1.3.1
## v readr   1.1.1     v forcats 0.3.0

## -- Conflicts ------------------------------------------
tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

if(!require(caret)) install.packages("caret", repos = "http://
cran.us.r-project.org")

## Loading required package: caret

## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift

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

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")

# 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,]

# Make sure userId and movieId in validation set are also in edx set
#validation 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", "genres")

edx <- rbind(edx, removed)

rm(dl, ratings, movies, test_index, temp, movielens, removed)
```

```
##########################################################################
#############
#################################################
```

before the analysis we check for any NA value

```
anyNA(edx)

## [1] FALSE
```

Data Summary and Explortory Data Analysis

After loading the data set we start by looking at the data structure and type we can see that there is six variable (userId, movieID, rating, timestamp, title, genres).as shown the year need to be separated from title if needed for prediction also the genres need separation if needed.

```
str(edx)

## 'data.frame':    9000055 obs. of  6 variables:
##  $ userId   : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ movieId  : num  122 185 292 316 329 355 356 362 364 370 ...
##  $ rating   : num  5 5 5 5 5 5 5 5 5 5 ...
##  $ timestamp: int  838985046 838983525 838983421 838983392
838983392 838984474 838983653 838984885 838983707 838984596 ...
##  $ title    : chr  "Boomerang (1992)" "Net, The (1995)" "Outbreak
(1995)" "Stargate (1994)" ...
##  $ genres   : chr  "Comedy|Romance" "Action|Crime|Thriller"
"Action|Drama|Sci-Fi|Thriller" "Action|Adventure|Sci-Fi" ...

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
##
##
##
```

from the summary of data we see that the minimum rating is 1 and max is 5 and the mean for the rating is 3.512 and the mode is 4.0.

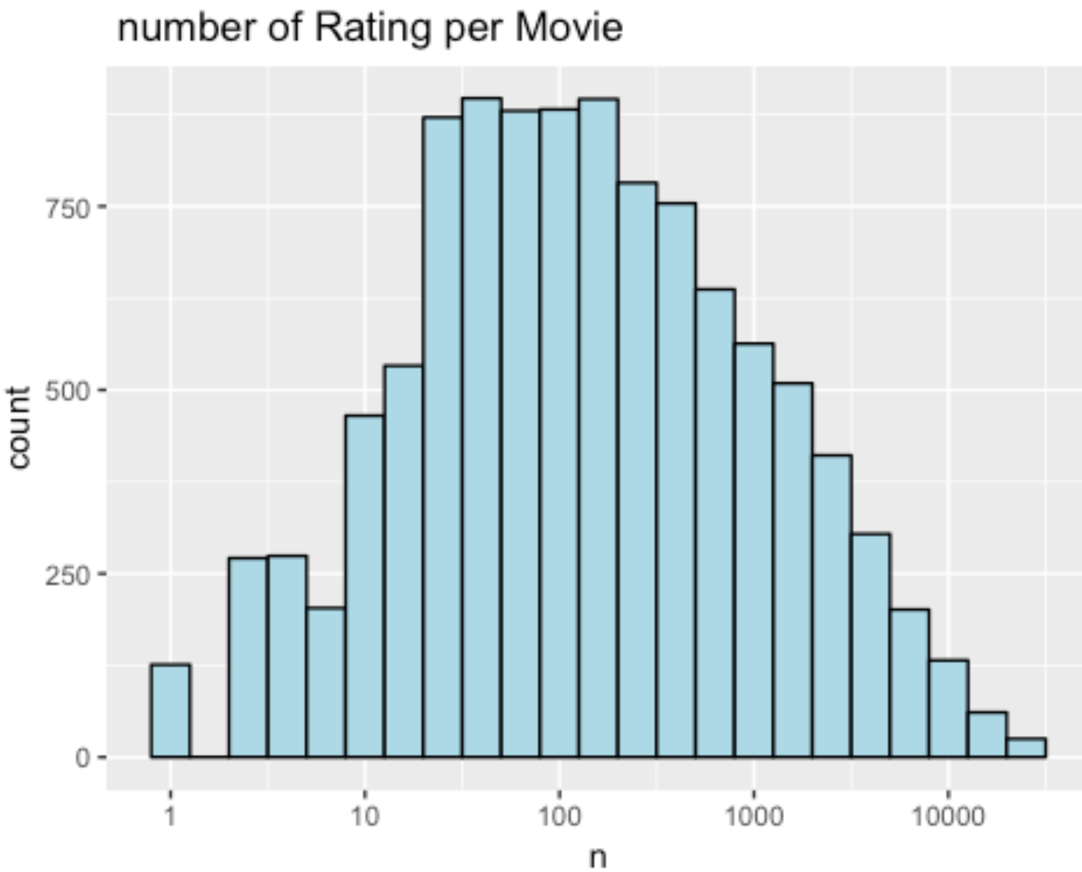
```
## Selecting by count

## # A tibble: 5 x 2
##   rating   count
##    <dbl>   <int>
## 1    4   2588430
## 2    3   2121240
## 3    5   1390114
## 4    3.5  791624
## 5    2    711422
```

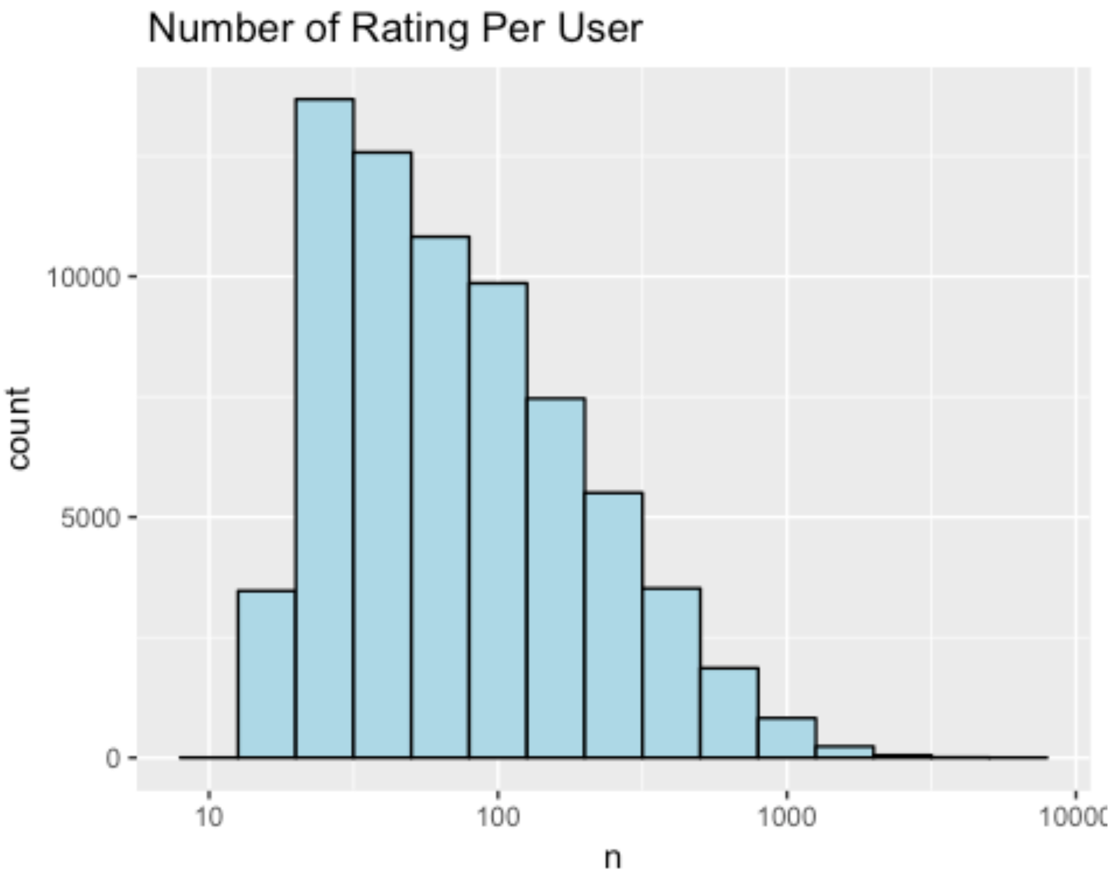
this code prints the number of unique movies and users in the data set:

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

to see how the number of ratings for every movie, we do that by plotting histogram

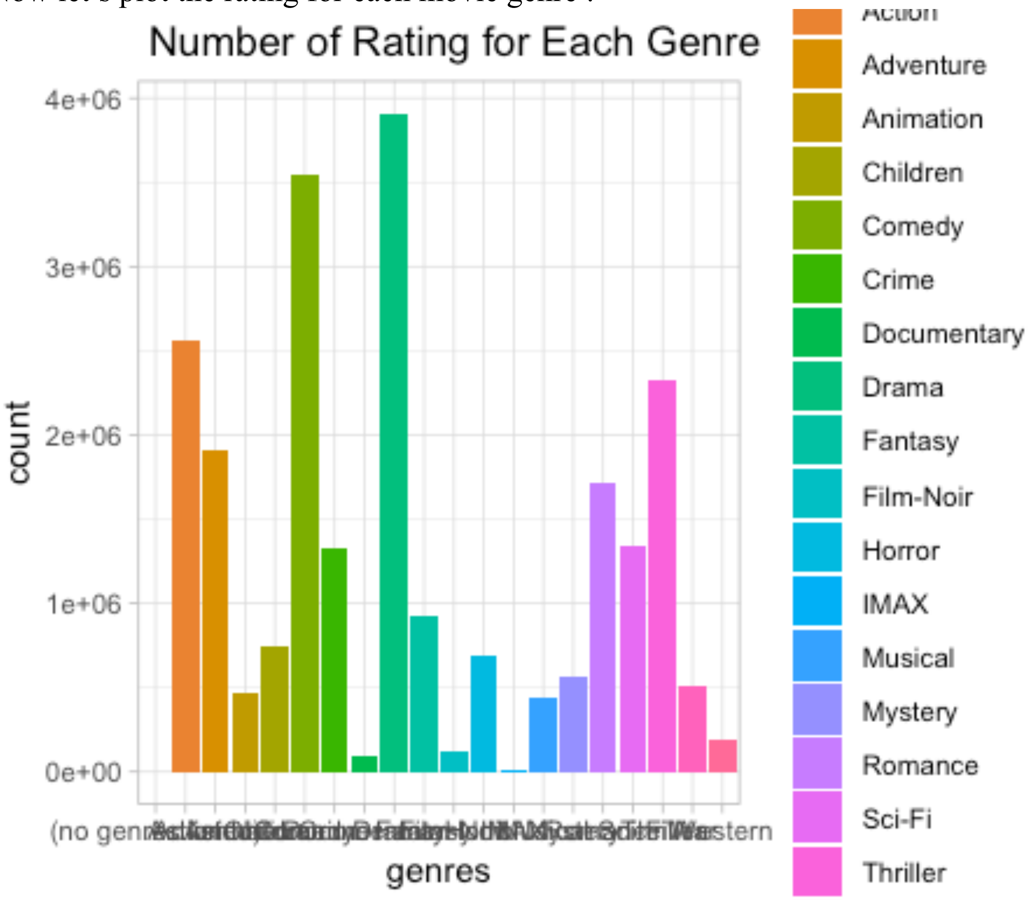


We note that some movies get more ratings it could be due to popularity. Now we visualize the number of ratings for each user



we see that some user are active more than others at rating movies.

Now let’s plot the rating for each movie genre :



let’s see the top 10 most popular genre

```
## # A tibble: 20 x 2
##    genres              count
##    <chr>               <int>
##  1 Drama             3910127
##  2 Comedy            3540930
##  3 Action            2560545
##  4 Thriller          2325899
##  5 Adventure         1908892
##  6 Romance           1712100
##  7 Sci-Fi            1341183
##  8 Crime             1327715
##  9 Fantasy            925637
```

```
## 10 Children               737994
## 11 Horror                 691485
## 12 Mystery                568332
## 13 War                    511147
## 14 Animation              467168
## 15 Musical                433080
## 16 Western                189394
## 17 Film-Noir              118541
## 18 Documentary             93066
## 19 IMAX                     8181
## 20 (no genres listed)          7
```

Data Partitioning

Before building the model we partition the edx data set into 20% for test set and 80% for the training set.

```
set.seed(1)
test_index <- createDataPartition(y = edx$rating, times = 1, p = 0.2,
list = FALSE)
train_set <- edx[-test_index,]
test_set <- edx[test_index,]
```

To make sure we don't include users and movies in the test set that do not appear in the training set, we remove these entries using the semi_join function:

```
test_set <- test_set %>%
  semi_join(train_set, by = "movieId") %>%
  semi_join(train_set, by = "userId")
```

Model building and RMSE calculation

The Netflix challenge used typical error loss. They decided on a winner based on the residual mean squared error (RMSE) on a test set. The RMSE will be the measure of accuracy.

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

First Model

In the first model, we predict the same rating for all movies regardless of the user. a model that assumes the same rating for all movies and users. no bias are considered here. this method assumes the following linear equation is true: $Y\ u, i\ = \mu + \varepsilon\ u, i$

```
Mu_1 <- mean(train_set$rating)
Mu_1

## [1] 3.512482

naive_rmse <- RMSE(test_set$rating,Mu_1)
naive_rmse

## [1] 1.059904
```

this code creates a table for the RMSE result to store all the result from each method to compare.

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

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

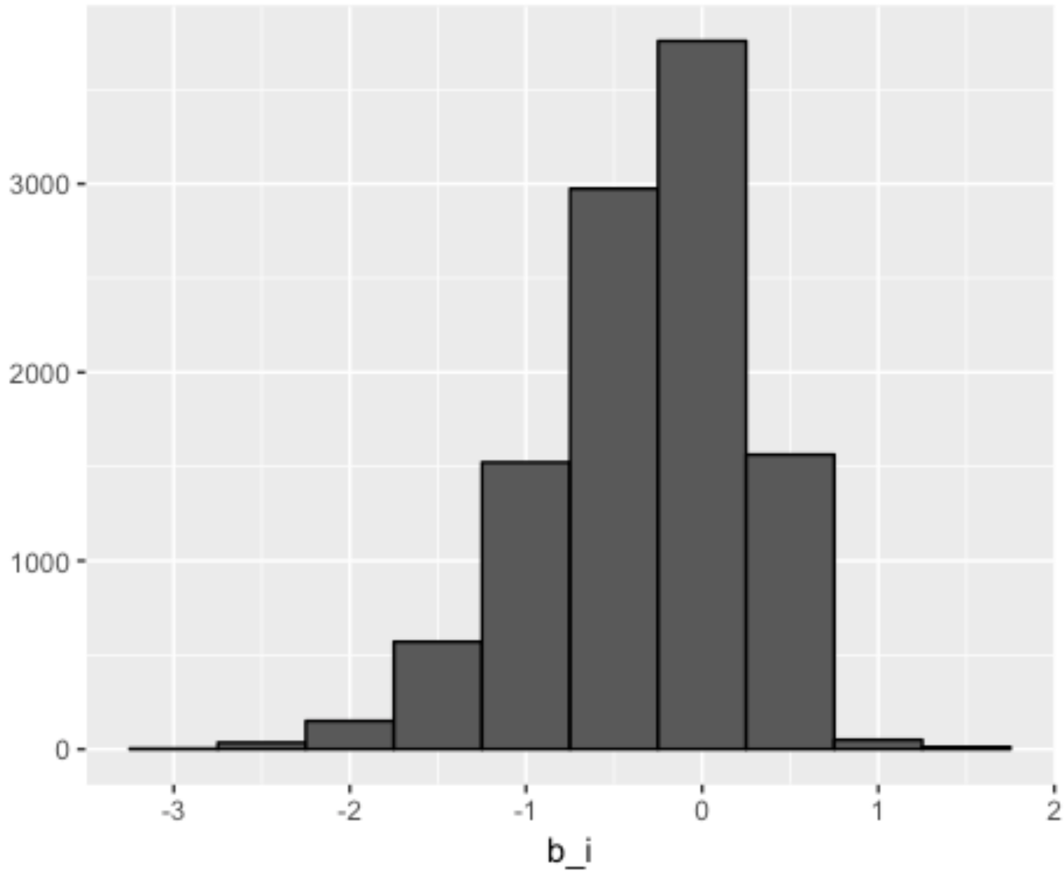
Second Model| Movie Effect

As we saw on the exploratory analysis some movies are rated more than other we can augment our previous model by adding the term $b\ i$ to represent the average ranking for movie i We can again use least squared to estimate considering the movie bias, in statics they refer to b as effect but in the Netflix paper referred them as "Bias" $Y\ u, i\ = \mu + b\ i\ + \varepsilon\ u, i$ Because there are thousands $b\ i$, each movie gets one, the lm() function will be very slow here. so we compute it using the average this way :

```
Mu_2 <- mean(train_set$rating)
movie_avgs <- train_set %>%
```

```r
  group_by(movieId) %>%
  summarize(b_i = mean(rating - Mu_2))
```

we can see that variability in the estimate as plotted here



let's see how the prediction improves after altering the equation $Y u,i = \mu + b\ i$

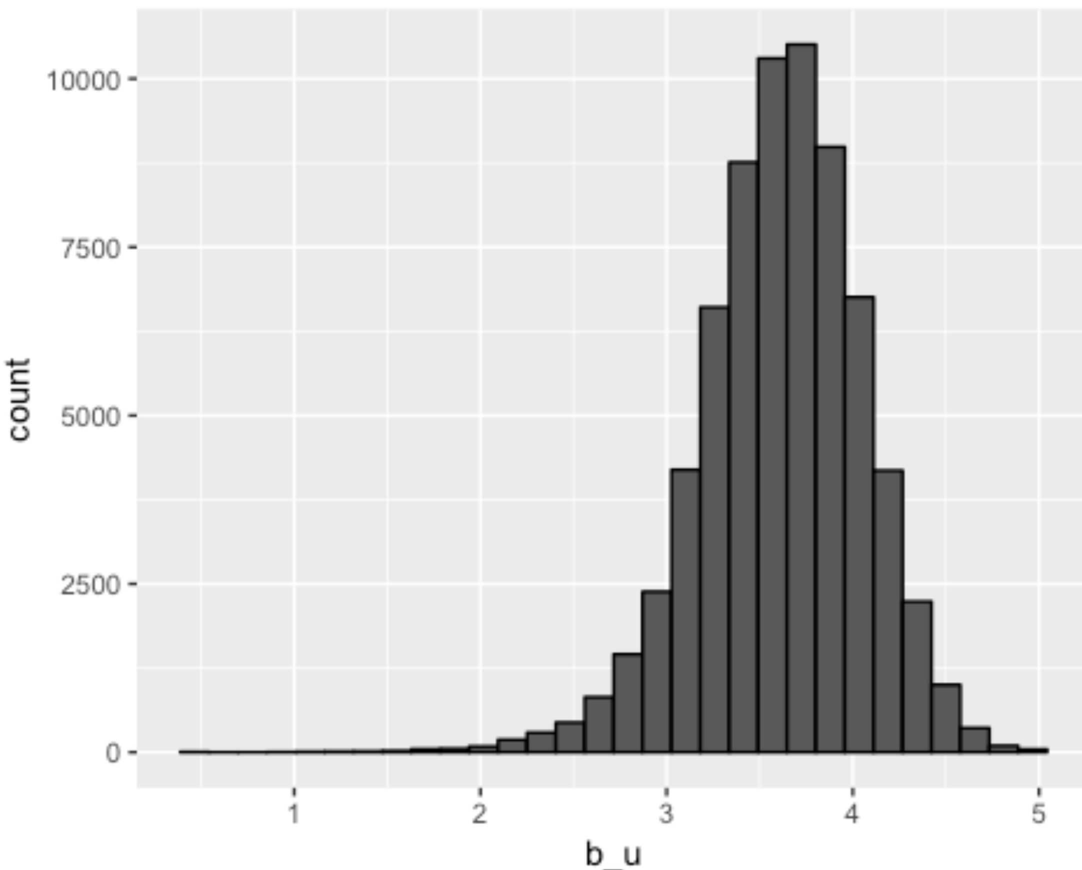
```r
predicted_ratings <- Mu_2 + test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  pull(b_i)

model_2_rmse <- RMSE(predicted_ratings, test_set$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie Effect Model",
                                     RMSE = model_2_rmse))
rmse_results
```

```
## # A tibble: 2 x 2
##   method              RMSE
##   <chr>              <dbl>
## 1 Just the average   1.06
## 2 Movie Effect Model 0.944
```

Third Model| User Effect

let's compure the user u for , for those who rated over 100 movies.



Notice that there is substantial variability across users ratings as well. This implies that a further improvement to our model may be $Y u, i \ = \mu + b\ i \ + \varepsilon\ u, i$ we could fit this model by using use the lm() function but as mentioned earlier it would be very slow $lm(rating\ as.factor(movieId) + as.factor(userId))$ so here is the code

```
user_avgs <- train_set %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u = mean(rating - Mu_2 - b_i))
```

now let’s see how RMSE improved this time

```
predicted_ratings <- test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  mutate(pred = Mu_2 + b_i + b_u) %>%
  pull(pred)


model_3_rmse <- RMSE(predicted_ratings, test_set$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie + User Effects
Model",
                                     RMSE = model_2_rmse))
rmse_results
```

```
## # A tibble: 3 x 2
##   method                      RMSE
##   <chr>                      <dbl>
## 1 Just the average           1.06
## 2 Movie Effect Model         0.944
## 3 Movie + User Effects Model 0.944
```

RMSE of the validation set

```
valid_pred_rating <- validation %>%
  left_join(movie_avgs, by = "movieId" ) %>%
  left_join(user_avgs , by = "userId") %>%
  mutate(pred = Mu_2 + b_i + b_u ) %>%
  .$pred
model_3_valid <- RMSE(validation$rating , valid_pred_rating)
```

```
rmse_results <- bind_rows( rmse_results, data.frame(Method =
"Validation Results" , RMSE = model_3_valid))
rmse_results
```

```
## # A tibble: 4 x 3
##   method                          RMSE Method
##   <chr>                          <dbl> <fct>
## 1 Just the average               1.06  <NA>
## 2 Movie Effect Model             0.944 <NA>
## 3 Movie + User Effects Model     0.944 <NA>
## 4 <NA>                          NA     Validation Results
```

Conclusion

I have developed a naive approach, movie effect and user + movie effect the best RMSE given by the third model. For further analysis more complicated prediction using the release year of the movie as a bias considering old movies such as the 60 or 80 periods as another genre for a better predicting model. A linear model for precision is recommended.