Movie Rating Prediction

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#Movie Rating Prediction

##Introduction

This report presents a prediction model to predict the rating on a MovieLense Dataset. This data set contains 10000054 ratings and 95580 tags applied to 10681 movies by 71567 users of the online movie recommender service MovieLens. Users were selected at random for inclusion. All users selected had rated at least 20 movies. Each user is represented by an id, and no other information is provided. The data are contained in three files, movies.dat, ratings.dat and tags.dat. More details about the contents and use of all these files can be found on (https://grouplens.org/datasets/movielens/10m/). To predict user ratings, a linear model was proposed that takes into consideration average rating, user average rating and movie average rating. Then a regularization effect is added to the model that adds a penalty to low number rating compared to high numbers which improve the RMSE results. Finally, the model is further optimized by tuning the weight of user and movie effects on rating prediction.

##Method and Analysis

In this section, we will start with data preparation, by downloading the dataset, creating training and validation set, clean the data. Then we will explore the data by viewing effect of movie and users on rating. Later, modeling the prediction and optimizing the model will take place.

###Data Preparation

First lets download and install required libraries.

```
## Loading required package: tidyverse

## -- Attaching packages --------------------------------- tidyverse 1.3.0 --

## v ggplot2 3.3.0     v purrr   0.3.3
## v tibble  3.0.0     v dplyr   0.8.5
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0

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

## Loading required package: caret

## Loading required package: lattice

##
## Attaching package: 'caret'

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

## Loading required package: data.table
```

```
##
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

## The following object is masked from 'package:purrr':
##
##     transpose
```

Now lets download the Dataset.

Creating partitions as follows 90% training and 10% Validation set.

```r
# Validation set will be 10% of MovieLens data
set.seed(1, sample.kind="Rounding")
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, list = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]
```

###Data Cleaning When preparing the validation set we must make sure that all users and movies in the training set (edx) are presented in the validation set then clear the R memory fom unnecessary objects.

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

Exploratory Data Analysis

After preparing the data let's have a look on its structure of the datasets.

```r
# edx Dataset dimension
print(paste("edx rows=",nrow(edx)))
```

```
## [1] "edx rows= 9000055"
```

```r
print(paste("edx cols=",ncol(edx)))
```

```
## [1] "edx cols= 6"
```

```r
print(paste("edx names=",names(edx)))
```

```
## [1] "edx names= userId"    "edx names= movieId"   "edx names= rating"
## [4] "edx names= timestamp" "edx names= title"     "edx names= genres"
```

```r
# number of zero ratings
print(paste("number of zero ratings"))
```

```
## [1] "number of zero ratings"
```

```r
print(sum(edx$rating==0))
```

```
## [1] 0
```

```r
# Number of unique Movies
print(paste("Number of unique Movies"))
```

```
## [1] "Number of unique Movies"
```

```r
print(length(unique(edx$movieId)))
```

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

```r
# Number of Uniqe Users
print(paste("Number of Users"))
```

```
## [1] "Number of Users"
```

```r
print(length(unique(edx$userId)))
```

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

```r
# Max number of rating
print(paste("Max number of ratings"))
```

```
## [1] "Max number of ratings"
```

```r
edx %>% group_by(movieId,title) %>% filter(n() > 2000) %>% summarize(count=n()) %>% arrange(desc(count))
```

```
## # A tibble: 10 x 3
## # Groups:   movieId [10]
##    movieId title                                                     count
##      <dbl> <chr>                                                     <int>
##  1     296 Pulp Fiction (1994)                                       31362
##  2     356 Forrest Gump (1994)                                       31079
##  3     593 Silence of the Lambs, The (1991)                          30382
##  4     480 Jurassic Park (1993)                                      29360
##  5     318 Shawshank Redemption, The (1994)                          28015
##  6     110 Braveheart (1995)                                         26212
##  7     457 Fugitive, The (1993)                                      25998
##  8     589 Terminator 2: Judgment Day (1991)                         25984
##  9     260 Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977) 25672
## 10     150 Apollo 13 (1995)                                          24284
```

```r
#Most Givin Ratings
print(paste("Most Givin Ratings"))
```

```
## [1] "Most Givin Ratings"
```

```r
edx %>% group_by(rating) %>% summarize(count=n()) %>% arrange(desc(count))%>% head(10)
```

```
## # A tibble: 10 x 2
##    rating   count
##     <dbl>   <int>
##  1    4   2588430
##  2    3   2121240
##  3    5   1390114
##  4    3.5  791624
##  5    2    711422
##  6    4.5  526736
##  7    1    345679
##  8    2.5  333010
##  9    1.5  106426
## 10    0.5   85374
```

Prepare Data for Modeling

Before start modeling on edx dataset, lets repartition it into training and test set. This is necessary since we will preserve the validation set just for final validation of our model.

```r
# Partition dataset to test and training
set.seed(2020,sample.kind = "Rounding")
test_index <- createDataPartition(y = edx$rating, times = 1,
                                  p = 0.2, list = FALSE)
train_set <- edx[-test_index,]
test_set <- edx[test_index,]

# The train set and the trest set considered without NA's
print(sum(is.na(edx$rating)))
```

```
## [1] 0
```

```r
# Now Lets filter only records that are in the train set
test_set <- test_set %>%
  semi_join(train_set, by = "movieId") %>%
  semi_join(train_set, by = "userId")
```

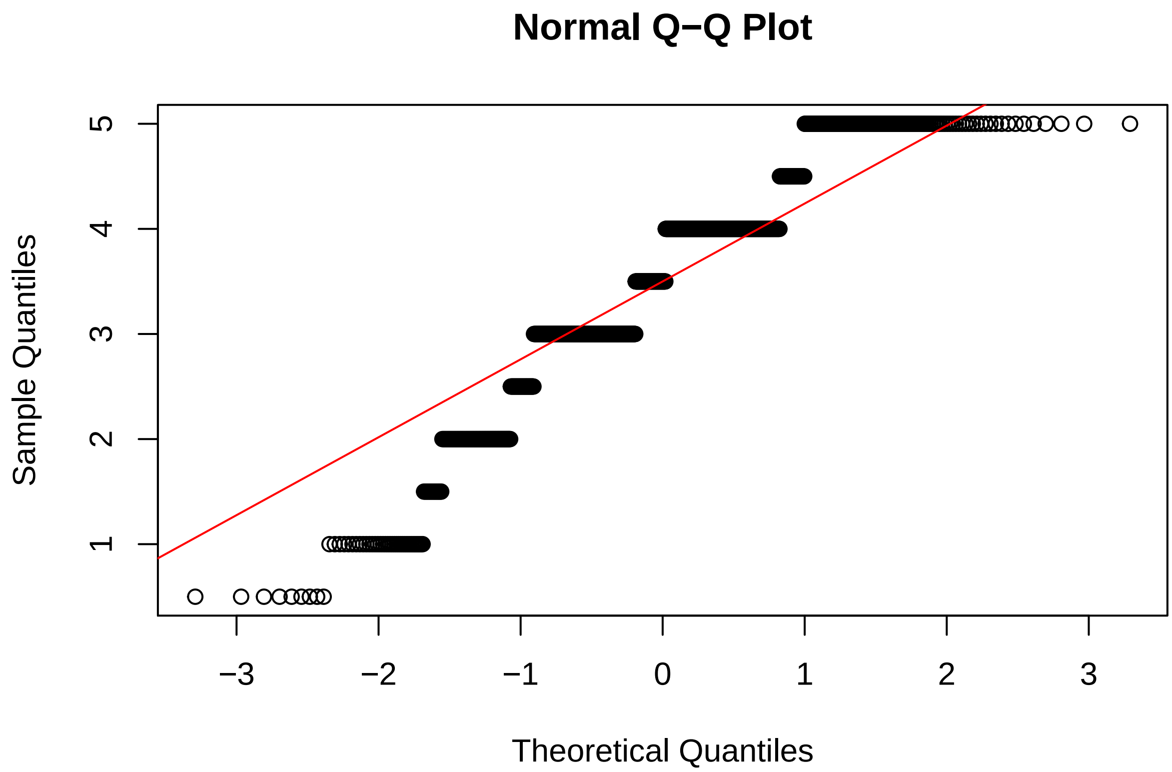
At this point we will define our RMSE function for validation and test purposes as follows.

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

Data Visualization

To have an idea about the distribution of the rating data, a quantile plot is useful at this point.

```r
# Lets sample 1000 sample from the training set to explore the distribution.

SampleIndex <- sample(1:nrow(train_set),1000)
SampleSet <- train_set[SampleIndex,]

# Plot the Quantile
qqnorm(SampleSet$rating);qqline(SampleSet$rating, col = 2)
```



Insights Gained

Regarding the quantile plot, it is obvious that the distribution of rating is somehow normal. This finding motivates us to think with a linear model that centred to the mean of the ratings.

Modeling

We will start with a basic model that takes into consideration just the mean of the rating as a predictor and have a look at the RMSE. Then we will update our model step by step to improve the RMSE.

```
# Use Just the Average as a prediction Model
mu<- mean(train_set$rating)
naive_rmse <- RMSE(test_set$rating, mu)
rmse_results <- data_frame(method = "Just the average", RMSE = naive_rmse)
```

Modeling rating by just the mean rating

```
## Warning: `data_frame()` is deprecated as of tibble 1.1.0.
## Please use `tibble()` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_warnings()` to see where this warning was generated.
```

```
# Show RMSE results
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.060572

Adding Movie effect (bi) to the Model The RMSE considering just the average rating is too high, we can improve this result by adding the movie effect (bi) to the model. This makes sense since famous Movies get a higher rating on average.

```
# Add Movie effect (bi) to Model the prediction
movie_avgs <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu))

# Predict rating on the test set
predicted_ratings <- mu + test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  .$b_i
# Calculating RMSE for this Model
model_1_rmse <- RMSE(predicted_ratings, test_set$rating)
# Adding results to the table of results
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie Effect Model",
                                     RMSE = model_1_rmse ))
# Showing the Results table
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076

Adding User Effect (bu) to the Model The addition of Movie effect to the model showes a slightly improvement in the RMSE.

```
# Add User effect bu to the Model

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

# Predicting based on the test set
predicted_ratings <- test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  mutate(pred = mu + b_i + b_u) %>%
  .$pred
# calculatin RMSE
model_2_rmse <- RMSE(predicted_ratings, test_set$rating)
# Adding Results to the table of results
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie + User Effects Model",
                                     RMSE = model_2_rmse ))
# Showing the Results table
```

```r
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076
Movie + User Effects Model	0.8661719

Lets explore the top 10 movies by rating.

```r
# Get Movie Titles
movie_titles <- edx %>%
  select(movieId, title) %>%
  distinct()
# Here we can see that the top movies has low number of ratings
train_set %>% dplyr::count(movieId) %>%
  left_join(movie_avgs) %>%
  left_join(movie_titles, by="movieId") %>%
  arrange(desc(b_i)) %>%
  select(title, b_i, n) %>%
  slice(1:10) %>%
  knitr::kable()
```

```
## Joining, by = "movieId"
```

title	b_i	n
Satan's Tango (SÃ¡tÃ¡ntangÃ³) (1994)	1.487502	1
Shadows of Forgotten Ancestors (1964)	1.487502	1
Fighting Elegy (Kenka erejii) (1966)	1.487502	1
Sun Alley (Sonnenallee) (1999)	1.487502	1
Pornographers, The (1966)	1.487502	1
Angus, Thongs and Perfect Snogging (2008)	1.487502	1
Human Condition III, The (Ningen no joken III) (1961)	1.237502	4
Titicut Follies (1967)	1.237502	2
Constantine's Sword (2007)	1.237502	2
More (1998)	1.154168	6

By exploring the movie's ranking it seems that the top 10 movies have a low number of rating. This effect can worsen the prediction. This brings us to apply regularization.

Adding Regularization to the Model

Regularization can be seen as to apply a penalty on low rating samples which will make the model rely on most on the high rating results.

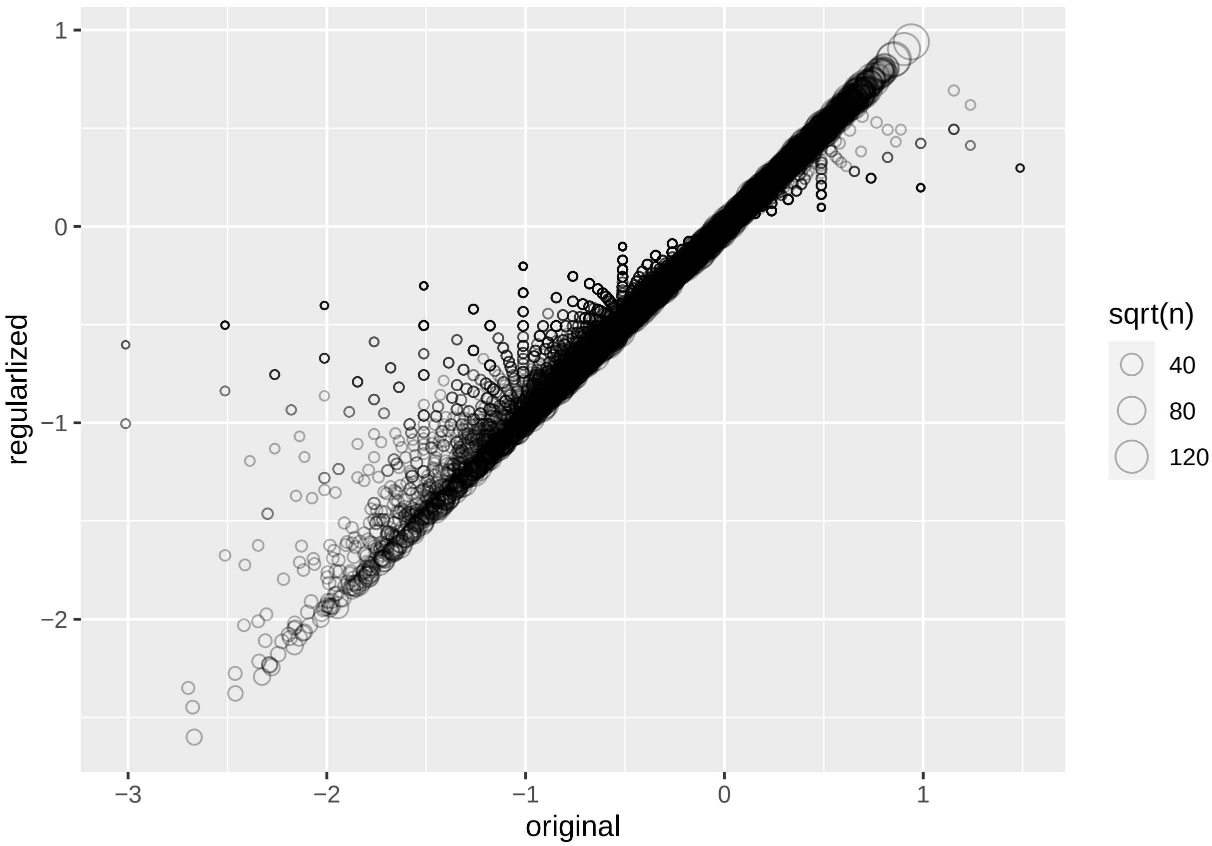
where lambda is a tuning parameter that can be chosen using cross-validation and Yu,I is the rating of user u on the movie i.

```r
# First lets chose an arbitrary lambda =4
lambda <- 4

movie_reg_avgs <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mu)/(n()+lambda), n_i = n())
```

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

We can show that the small samples n are more closed to zero by plotting original vs regularized ratings.

```
# plotting reularized vs original rating
tibble(original = movie_avgs$b_i,
           regularlized = movie_reg_avgs$b_i,
           n = movie_reg_avgs$n_i) %>%
  ggplot(aes(original, regularlized, size=sqrt(n))) +
  geom_point(shape=1, alpha=0.3)
```



Now Lets look at the top 10 movies after regularization

```
# Showing a table of the 10 top movies after regularization.
train_set %>%
  dplyr::count(movieId) %>%
  left_join(movie_reg_avgs) %>%
  left_join(movie_titles, by="movieId") %>%
  arrange(desc(b_i)) %>%
  select(title, b_i, n) %>%
  slice(1:10) %>%
  knitr::kable()
```

```
## Joining, by = "movieId"
```

title	b_i	n
Shawshank Redemption, The (1994)	0.9400115	22347
Godfather, The (1972)	0.9032235	14234
Schindler's List (1993)	0.8529655	18552
Usual Suspects, The (1995)	0.8477926	17278
Rear Window (1954)	0.8045807	6340
Casablanca (1942)	0.8035172	9059
Third Man, The (1949)	0.7988516	2344
Double Indemnity (1944)	0.7976888	1758
Seven Samurai (Shichinin no samurai) (1954)	0.7961988	4141
Paths of Glory (1957)	0.7943859	1267

The top 10 movies are more intuitive as they have higher sample size.

Lets Predict using the new regulized bi and bu

```
# Predict based on the new Model
  predicted_ratings <-
    test_set %>%
    left_join(movie_reg_avgs, by = "movieId") %>%
    left_join(user_reg_avgs, by = "userId") %>%
    mutate(pred = mu + b_i + b_u) %>%
    .$pred
# Calculating RMSE
model_3_rmse <- RMSE(predicted_ratings, test_set$rating)
# Adding Results to the Table
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Regularized bi + bu Model",
                                     RMSE = model_3_rmse ))
# Show table of results
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076
Movie + User Effects Model	0.8661719
Regularized bi + bu Model	0.8654959

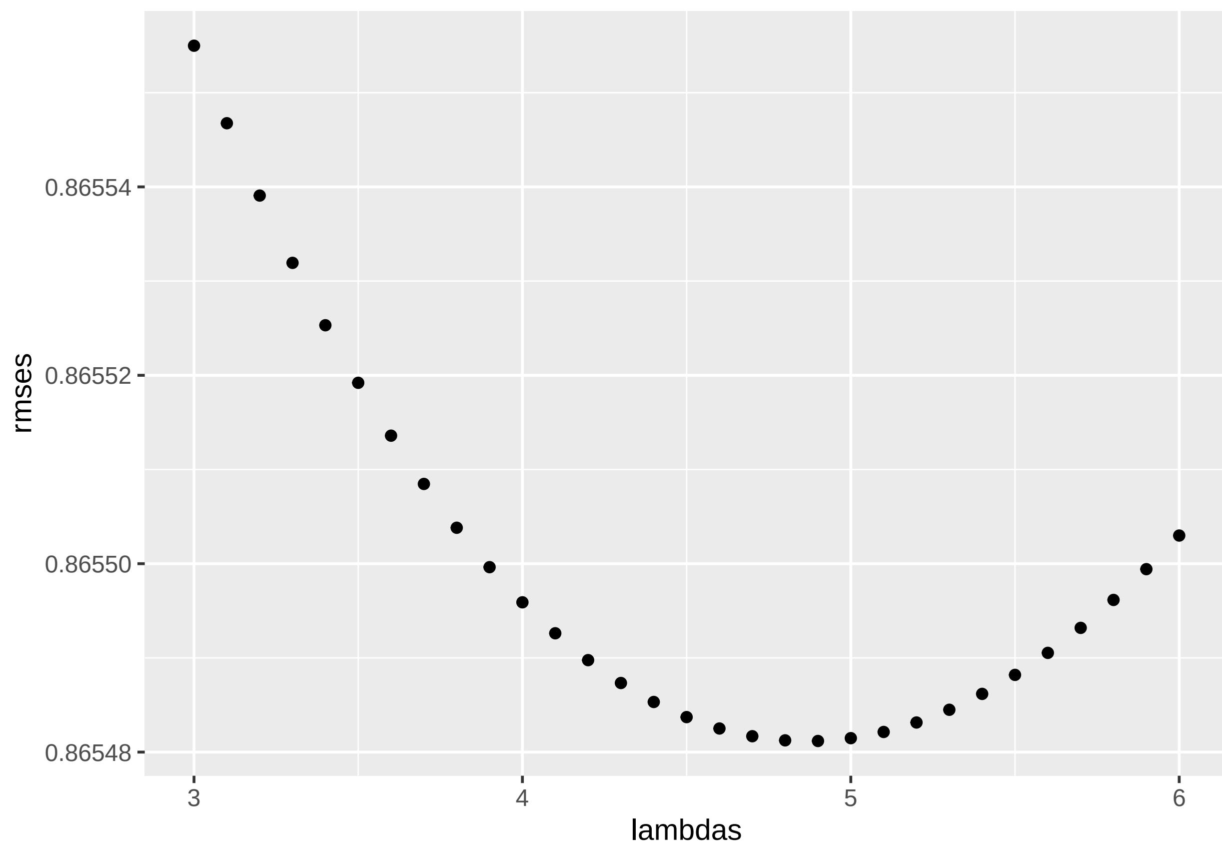
lets find the best Lambda by tuning parameters.

```
lambdas <- seq(3, 6, 0.1)
rmses <- sapply(lambdas, function(l){
  mu <- mean(train_set$rating)

movie_reg_avgs <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mu)/(n()+l), n_i = n())
#Note that, bi is calculated as the solution to minimize eq1
```

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

# Predict based on the new Model
  predicted_ratings <-
    test_set %>%
    left_join(movie_reg_avgs, by = "movieId") %>%
    left_join(user_reg_avgs, by = "userId") %>%
    mutate(pred = mu + b_i + b_u) %>%
    .$pred
  return(RMSE(predicted_ratings, test_set$rating))
})
```

The result can be shown in the following figure

```
# plot lambda
qplot(lambdas, rmses)
```




```
lmbdBest <- lambdas[which.min(rmses)]
print(paste("Best Lambda=",lambda))
```

```
## [1] "Best Lambda= 4"
```

Now lets add the best result to the result table

```r
#Add the final Model to the rmse result to compare Models
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Regularized bi + bu, Best  ",
                                     RMSE = min(rmses)))
# Show table of results
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076
Movie + User Effects Model	0.8661719
Regularized bi + bu Model	0.8654959
Regularized bi + bu, Best <U+03BB>	0.8654812

Filtering out layers

Since rating is a number between 0 and 5 we can limit the prediction to this interval and round the outlayers to the nearest limit

```r
movie_reg_avgs <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mu)/(n()+lmbdBest), n_i = n())
#Note that, bi is calculated as the solution to minimize eq1

user_reg_avgs <- train_set %>%
  left_join(movie_reg_avgs, by="movieId") %>%
  group_by(userId) %>%
  summarize(b_u = sum(rating - b_i - mu)/(n()+lmbdBest))

# Predict based on the new Model
  predicted_ratings <-
    test_set %>%
    left_join(movie_reg_avgs, by = "movieId") %>%
    left_join(user_reg_avgs, by = "userId") %>%
    mutate(pred_raw = mu + b_i + b_u) %>%
    mutate(pred=case_when(pred_raw < 0 ~ 0, pred_raw >5 ~5, TRUE ~ pred_raw )) %>%
    .$pred
# calculatin RMSE
model_4_rmse <- RMSE(predicted_ratings, test_set$rating)
#Add the final Model to the rmse result to compare Models
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="After Filtering Outlayer",
                                     RMSE =model_4_rmse ))
# Show table of results
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076
Movie + User Effects Model	0.8661719
Regularized bi + bu Model	0.8654959
Regularized bi + bu, Best <U+03BB>	0.8654812

method	RMSE
After Filtering Outlayer	0.8653797

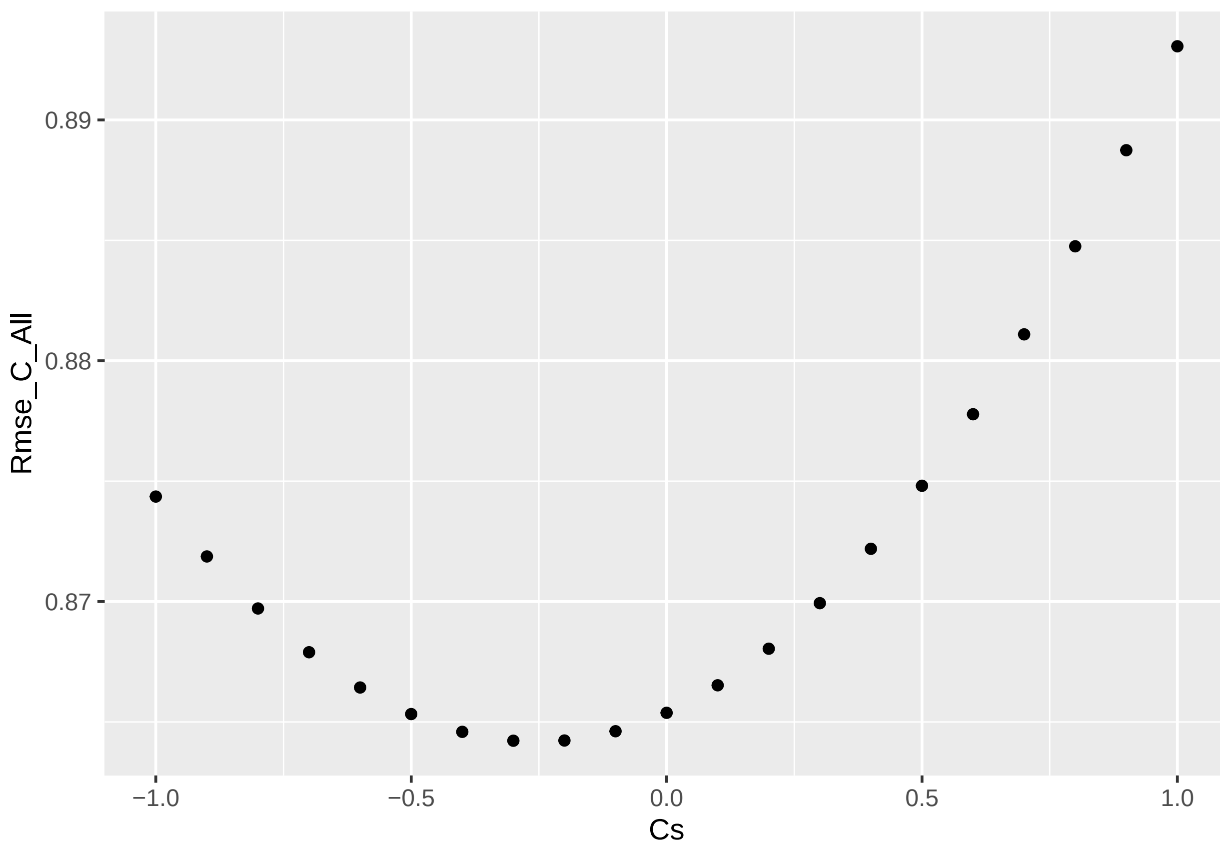
Adding Weighted mutual effect of movie and user to the model

We can further optimize our model by adding weight to the user effect and movie effect and tune those weights to get better RMSE. According to the foloowing formula: y= mu + b_i + b_u + (C) * b_u * b_i Where C is weight tuning parameter.

```
Cs <-seq (-1,1,0.1)
Rmse_C_All <- sapply( seq(-1,1,0.1), function(c){
# Predict based on the new Model
  predicted_ratings <-
    test_set %>%
    left_join(movie_reg_avgs, by = "movieId") %>%
    left_join(user_reg_avgs, by = "userId") %>%
    mutate(pred_raw = mu + b_i + b_u + (c)*b_u*b_i) %>%
    mutate(pred=case_when(pred_raw < 0 ~ 0, pred_raw > 5 ~5, TRUE ~ pred_raw )) %>%
    .$pred
# calculatin RMSE
RMSE(predicted_ratings, test_set$rating)
})
```

Plotting mutual weight

```
# plot mutual Weight
qplot(Cs, Rmse_C_All)
```



```
CBest <- Cs[which.min(Rmse_C_All)]
print(paste("Best C=",CBest ))
```

```
## [1] "Best C= -0.3"
```

```
# Predict based on the new Model
  predicted_ratings <-
    test_set %>%
    left_join(movie_reg_avgs, by = "movieId") %>%
    left_join(user_reg_avgs, by = "userId") %>%
    mutate(pred_raw = mu + b_i + b_u + (CBest)*b_u*b_i) %>%
    mutate(pred=case_when(pred_raw < 0 ~ 0, pred_raw > 5 ~5, TRUE ~ pred_raw )) %>%
    .$pred
# calculatin RMSE
model_5_rmse <- RMSE(predicted_ratings, test_set$rating)
#Add the final Model to the rmse result to compare Models
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="After Optimizing mutual weight",
                                     RMSE =model_5_rmse ))
# Show table of results
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076
Movie + User Effects Model	0.8661719
Regularized bi + bu Model	0.8654959
Regularized bi + bu, Best <U+03BB>	0.8654812
After Filtering Outlayer	0.8653797
After Optimizing mutual weight	0.8642217

Results

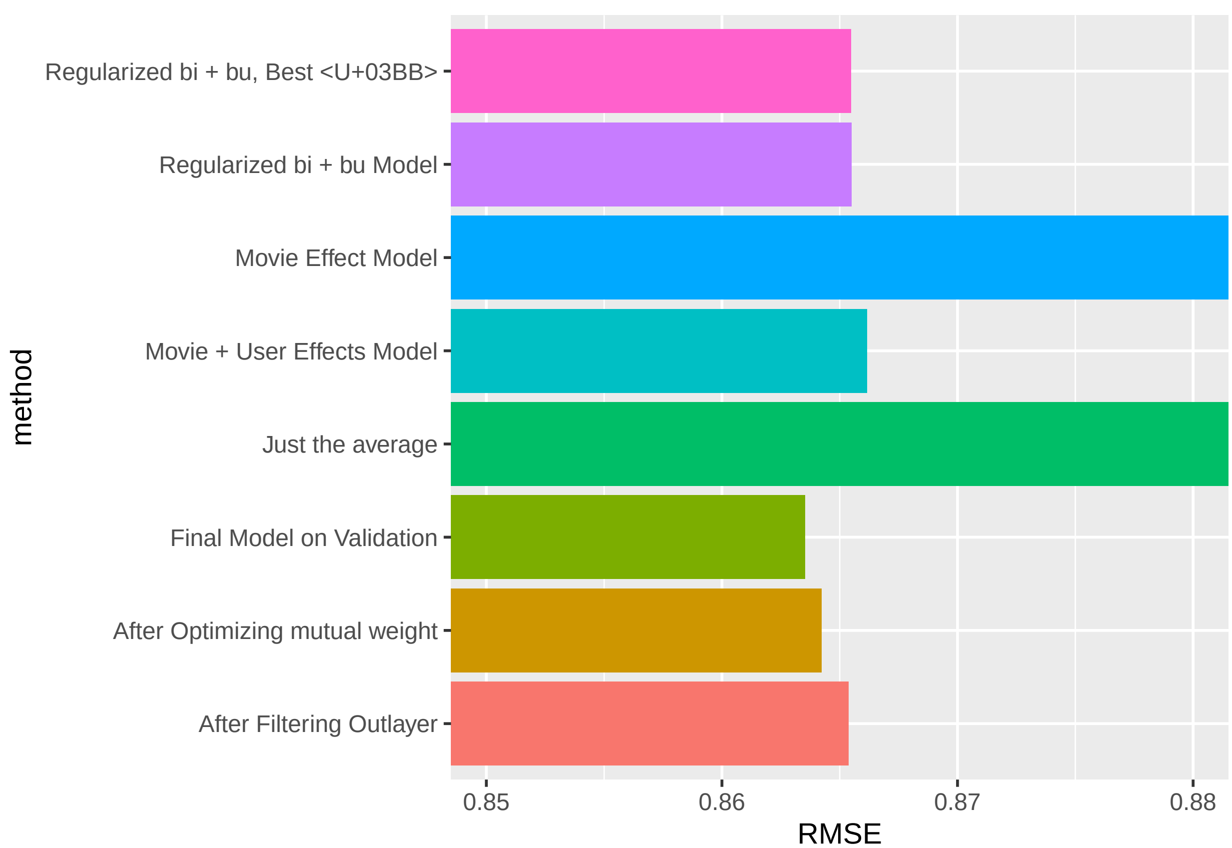
After finding a good model, now we are ready to apply the final model on the validation set. In addition we can use all the edx dataset for training,

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

movie_reg_avgs <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mu)/(n()+lmbdBest), n_i = n())
#Note that, bi is calculated as the solution to minimize eq1

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

# Predict based on the Final model using Validation Datase
  predicted_ratings <-
    validation %>%
    left_join(movie_reg_avgs, by = "movieId") %>%
    left_join(user_reg_avgs, by = "userId") %>%
    mutate(pred_raw = mu + b_i + b_u + (CBest)*b_u*b_i) %>%
```

```
    mutate(pred=case_when(pred_raw < 0 ~ 0, pred_raw > 5 ~5, TRUE ~ pred_raw )) %>%
    .$pred
# calculatin RMSE
model_6_rmse <- RMSE(predicted_ratings, validation$rating)
#Add the final Model to the rmse result to compare Models
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Final Model on Validation",
                                     RMSE =model_6_rmse ))
# Show table of results
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0605725
Movie Effect Model	0.9437076
Movie + User Effects Model	0.8661719
Regularized bi + bu Model	0.8654959
Regularized bi + bu, Best <U+03BB>	0.8654812
After Filtering Outlayer	0.8653797
After Optimizing mutual weight	0.8642217
Final Model on Validation	0.8635311

```
ggplot(rmse_results, aes(method,RMSE,fill=method )) + geom_bar(stat="identity") + theme(legend.position
```



Conclusion

By the conclusion, we had defined a predictive model that takes into consideration the general, average rating, movies biased rating and the user biased rating. Then we add regularization parameters that take into consideration the number of rating. The effect of the regulation had a significant effect on reducing the RMSE. In addition, the addition of the mutual effect weight had further improved the RMSE. For future work, further improvement can be done by using singular value decomposition and variable importance to focus on variables with high variability.