HarvardX: PH125.9x Data Science: Capstone Course

Movie Rating Prediction Project; Movie Lens Dataset

Bijal Ashwin Ved 12/28/2019

Contents

1 Introduction

The Movie Lens project forms part of the HarvardX: PH125.9x Data Science: Capstone course. It closely follows the Data Science textbook by Rafael Irizarry paricularly; Chapter 34.7 Recommendation systems, and Chapter 34.9 Regularization. The dataset was supplied as part of the course.

The aim of the project is to develop and train a recommendation machine learning algorithm to predict a rating given by a users to a movie in the dataset. The Residual Mean Square Error (RMSE) will be used to evaluate the accuracy of the algorithm. The required criteria for the projects is a RMSE lower than 0.8775.

This report will present an overview of the data, analysis, results and a conclusion.

1.1 Dataset

An introductory review of the dataset is performed in order to familiarise ourselves. Data is downloaded as per instruction from the MovieLens 10M dataset.

```
#############################################################################
## Create edx set, validation set
#############################################################################

# Note: this process could take a couple of minutes

# Package Installs
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")

# Libraries
library(tidyverse)
library(caret)
library(hexbin)

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

# Check for download
datafile <- "MovieLens.RData"
if(!file.exists("MovieLens.RData"))
{
  print("Download")
  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
```

```r
  set.seed(1, sample.kind = "Rounding") # if using R 3.6.0: 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,]

  # 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")

  # 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)
  save(edx, validation, file = datafile)

} else {
  load(datafile)
}
```

Edx dataset contains rows corresponding to an users rating of a movie. The set contains the vaiables; "userId", "movieId", "rating", "timestamp", "title", "genres".

```r
# Summarise Data
head(edx, 5)
```

```
##   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)
##                          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
```

Summarising the dataset reveals a well formatted set with no missing values. Movies are rated between 0.5 and 5.0, with 9000055 rows in total.

```r
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
##
##
##
```

The dataset contains ~10,700 unique movies, ~70,000 unique movies, and ~800 unique combinations of genres, and a mean movie rating of ~3.5 out of 5.

```r
# Movies, Users and Genres in Database
edx %>% summarise(
  uniq_movies = n_distinct(movieId),
  uniq_users = n_distinct(userId),
  uniq_genres = n_distinct(genres))
```

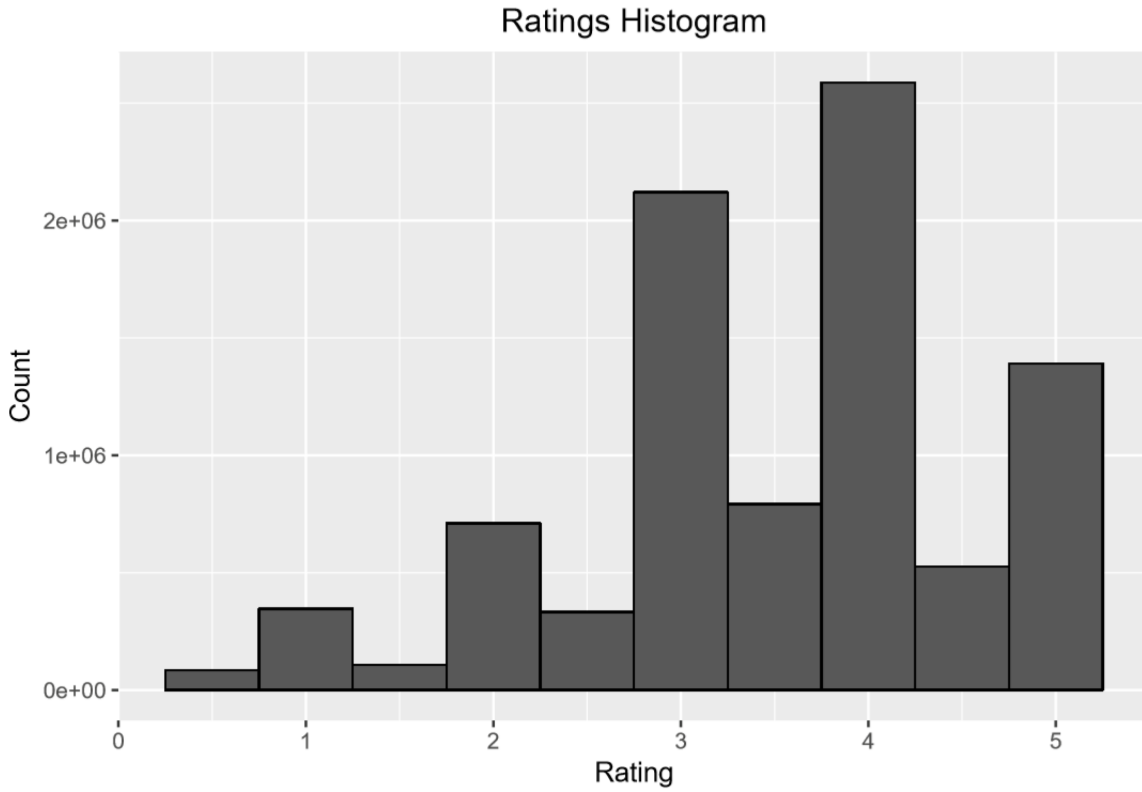
```
##   uniq_movies uniq_users uniq_genres
## 1       10677      69878         797
```

```r
# Ratings Mean
rating_mean <- mean(edx$rating)
rating_mean
```

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

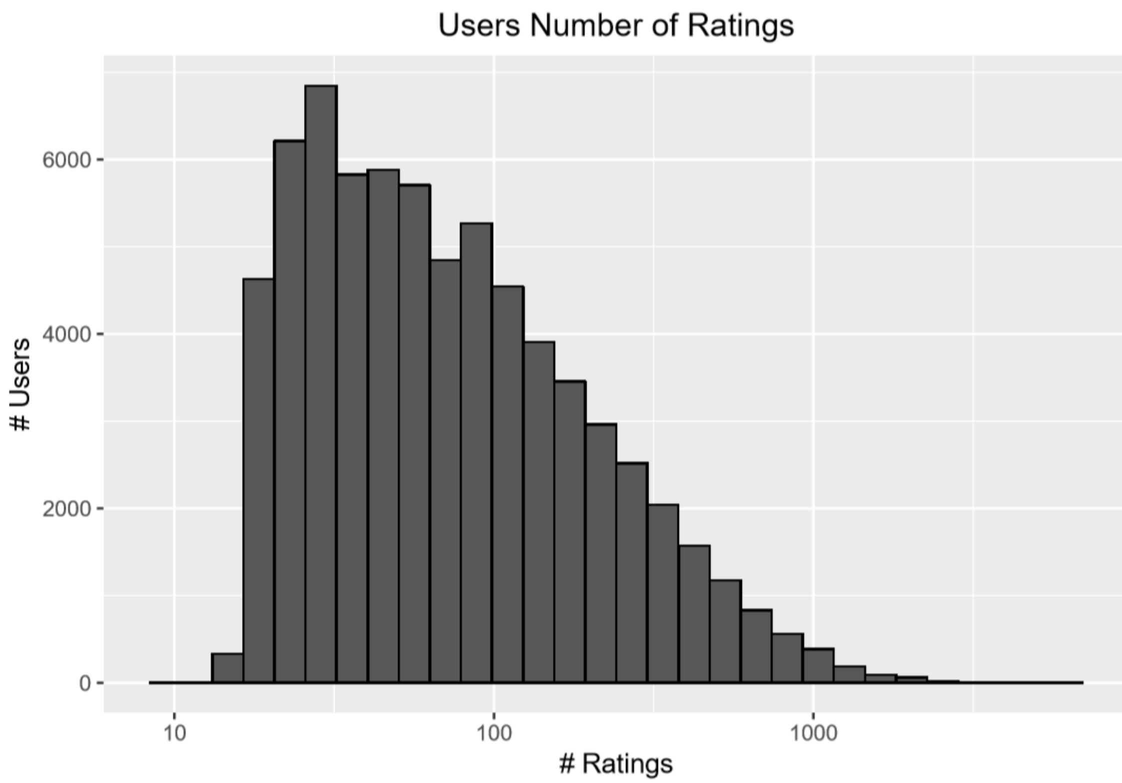
A histogram of the dataset mapping ratings and counts are below. The highest rating users give movies are, in decreasing order 4.0, 3.0, 5.0. Overall users rate movies higher in the ratings scale. Similarly, users are more likely to rate full ratings rather than half ratings on the scale.

```r
# Ratings Histogram
edx %>%
  ggplot(aes(rating)) +
  geom_histogram(binwidth = 0.5, color = "black") +
  xlab("Rating") +
  ylab("Count") +
  ggtitle("Ratings Histogram") +
  theme(plot.title = element_text(hjust = 0.5))
```



The majority of users rate between 10 and 100 movies, whilst some may rate over 1,000. Including a variable in the model to account for number of ratings should be discussed.

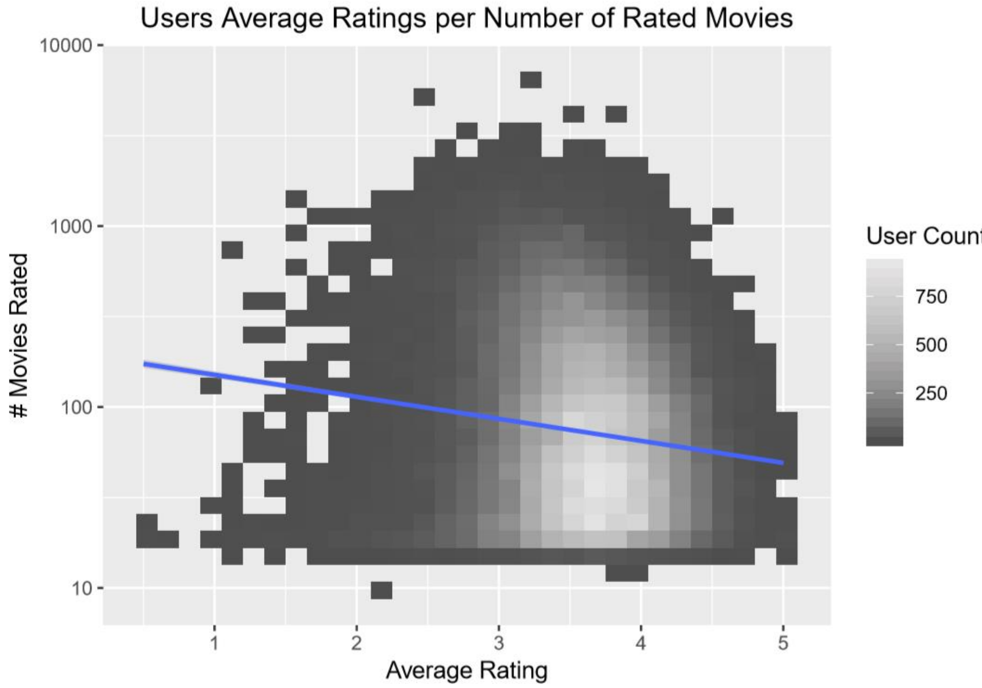
```
# Ratings Users - Number of Ratings
edx %>%
  count(userId) %>%
  ggplot(aes(n)) +
  geom_histogram(color = "black", bins=30) +
  scale_x_log10() +
  xlab("# Ratings") +
  ylab("# Users") +
  ggtitle("Users Number of Ratings") +
  theme(plot.title = element_text(hjust = 0.5))
```



A heatmap showing average movie rating against number of movies rated is plotted. The most common movies ratings and number of movies rated are hightlighted. This occurs for a rating between 3.5 and 4.0 and between 10 and 100 movies.

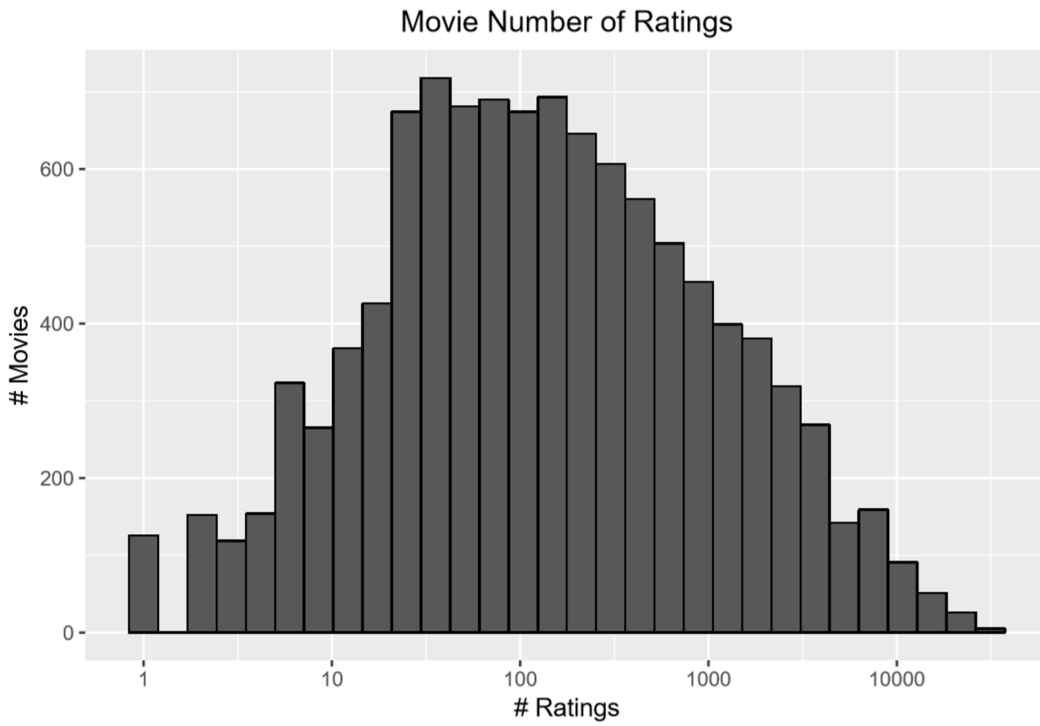
A linear curve was fitted to the data to show the overall trajectory of the ratings with number of movies rated. A more memory and calculation intensive curve fitting was attempted but unfortunately unable to run on the author's computer. The more ratings a user gives results in a lower mean rating.

```
# Ratings Users - Mean by Number with Curve Fitted
edx %>%
  group_by(userId) %>%
  summarise(mu_user = mean(rating), number = n()) %>%
  ggplot(aes(x = mu_user, y = number)) +
  geom_bin2d( ) +
  scale_fill_gradientn(colors = grey.colors(10)) +
  labs(fill="User Count") +
  scale_y_log10() +
  geom_smooth(method = lm) +
  ggtitle("Users Average Ratings per Number of Rated Movies") +
  xlab("Average Rating") +
  ylab("# Movies Rated") +
  theme(plot.title = element_text(hjust = 0.5))
```



The number of ratings for each movie are shown below in the histogram. A number of outlier movies have been rated less than 10 times which will make predicting future ratings more difficult.

```
# Ratings Movies - Number of Ratings
edx %>%
  count(movieId) %>%
  ggplot(aes(n)) +
  geom_histogram(color = "black", bins=30) +
  scale_x_log10() +
  xlab("# Ratings") +
  ylab("# Movies") +
  ggtitle("Movie Number of Ratings") +
  theme(plot.title = element_text(hjust = 0.5))
```


Movie Number of Ratings
Movies
600
400
200
0
1
10
100
1000
10000
Ratings

2 Analysis and Results

The Residual Mean Square Error (RMSE) is the error function to that will measure accuracy and quantify the typical error we make when predicting the movie rating. An error larger than 0.8775, it means our typical error is larger than the required for this assignment almost a star, which is not good. RMSE defined;

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

where; N is the number of users, movie ratings, and the sum incorporating the total combinations.

2.1 Simple Prediction Based on Mean Rating

The simple prediction model uses the mean of the dataset to predict the rating for all movies. The model assumes that all differences are due to a random error;

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

where $Y_{u,i}$ is the prediction, $\epsilon_{u,i}$ is the independent error, and μ the expected "true" rating for all movies. Predicting the mean gives the following naive RMSE.

```r
## Simple Prediction based on Mean Rating
mu <- mean(edx$rating)
mu
```

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

```r
rmse_naive <- RMSE(validation$rating, mu)
rmse_naive
```

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

```r
## Save Results in Data Frame
rmse_results = data_frame(method = "Naive Analysis by Mean", RMSE = rmse_naive)
```

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

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

method	RMSE
Naive Analysis by Mean	1.061202

Investigating the dataset allows for more advanced analysis and rating predictions with smaller error.

2.2 Movie Effects Model

The Movie Effects Model calculates a bias term for each movie based on the difference between the movies mean rating and the overall mean rating.

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

where $Y_{u,i}$ is the prediction, $\epsilon_{u,i}$ is the independent error, and μ the mean rating for all movies, and b_i is the bias for each movie i.

```r
## Simple model taking into account the movie effects, b_i

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

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

```r
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarise(b_i = mean(rating - mu))

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

rmse_model_movie_effects <- RMSE(predicted_ratings, validation$rating)
rmse_model_movie_effects
```

```
## [1] 0.9439087
```

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

method	RMSE
Naive Analysis by Mean	1.0612018
Movie Effects Model	0.9439087

The Movie Effect Model; predicting the movie rating with both bias, b_i, and mean, μ gives an improved prediction with a lower RMSE value.

2.3 Movie and User Effects Model

The next step is to incorporate the individual User Effects, b_u, in to the model. Acknowledging each user inherent bias to mark all films higher or lower.

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

where $Y_{u,i}$ is the prediction, $\epsilon_{u,i}$ is the independent error, and μ the mean rating for all movies, b_i is the bias for each movie i, and b_u is the bias for each user u.

```r
## Movie and User Effects Model
# Simple model taking into account the user effects, b_u
user_avgs <- edx %>%
  left_join(movie_avgs, by="movieId") %>%
  group_by(userId) %>%
  summarise(b_u = mean(rating - mu - b_i))

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

```r
rmse_model_user_effects <- RMSE(predicted_ratings, validation$rating)
rmse_model_user_effects
```

```
## [1] 0.8653488
```

```r
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie and User Effects Model",
                                     RMSE = rmse_model_user_effects))
rmse_results %>% knitr::kable()
```

method	RMSE
Naive Analysis by Mean	1.0612018
Movie Effects Model	0.9439087
Movie and User Effects Model	0.8653488

Incorporating the user bias into the model resulted in a further reduced RMSE.

2.4 Regularisation

Regularisation allows for reduced errors caused by movies with few ratings which can influence the prediction and skew the error metric. The method uses a tuning parmeter, λ, to minimise the RMSE. Modifying b_i and b_u for movies with limited ratings.

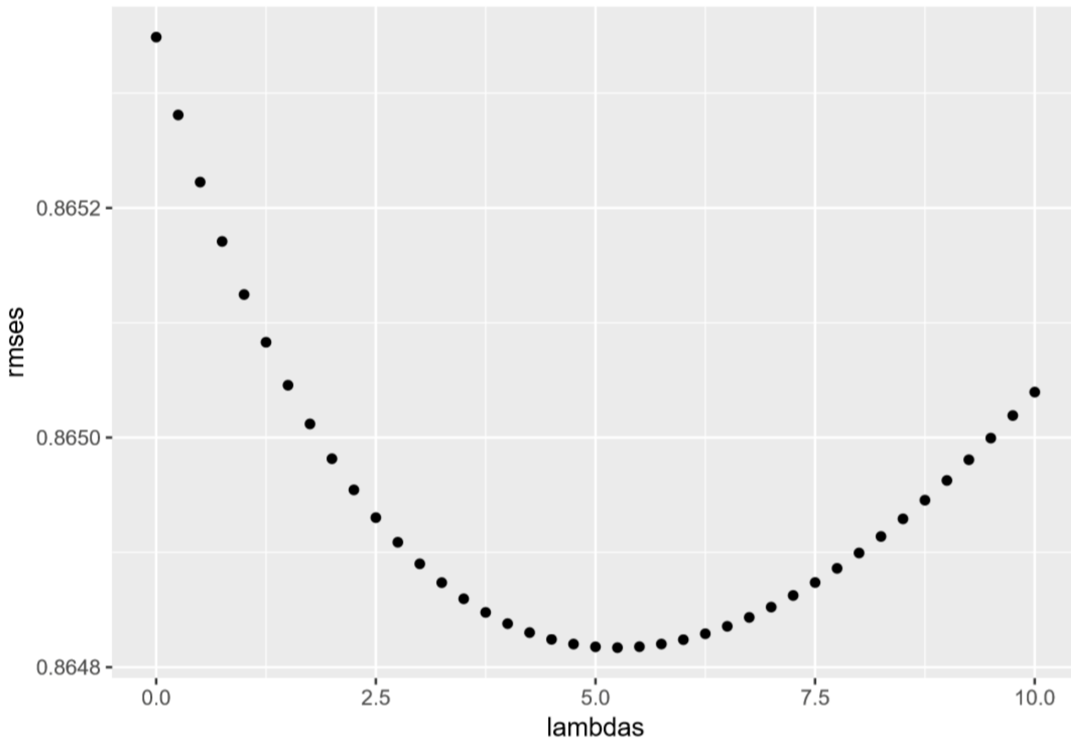
$$Y_{u,i} = \mu + b_{i,n,\lambda} + b_{u,n,\lambda} + \epsilon_{u,i}$$

```r
# Predict via regularisation, movie and user effect model
# (as per https://rafalab.github.io/dsbook 34.9 Regularization)

lambdas <- seq(0, 10, 0.25)
rmses <- sapply(lambdas, function(l){

  mu <- mean(edx$rating)

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

  b_u <- edx %>%
    left_join(b_i, by="movieId") %>%
    group_by(userId) %>%
    summarise(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))

})
```

```r
rmse_regularisation <- min(rmses)
rmse_regularisation
```

```
## [1] 0.864817
```

```r
# Plot RMSE against Lambdas to find optimal lambda
qplot(lambdas, rmses)
```




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

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

```r
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Regularised Movie and User Effects Model",
                                     RMSE = rmse_regularisation))
rmse_results %>% knitr::kable()
```

method	RMSE
Naive Analysis by Mean	1.0612018
Movie Effects Model	0.9439087
Movie and User Effects Model	0.8653488
Regularised Movie and User Effects Model	0.8648170

Regulisation of a Movie and User Effect model has lead to a lowest RMSE of the prediction methods for the MovieLens ratings system.

3 Results and Discussion

The final values of the prediction models are shown below;

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

method	RMSE
Naive Analysis by Mean	1.0612018
Movie Effects Model	0.9439087
Movie and User Effects Model	0.8653488
Regularised Movie and User Effects Model	0.8648170

The models from most accurate to least accurate are as follows; Regularised Movie and User Effects Model; Movie and User Effects Model; Movie Effects Model; and Simple Average Model.

The final model optimised for the prediction is the following;

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

The lowest value of RMSE predicted is 0.8648170.

4 Conclusion

A machine learning alogorithm to predict the ratings from the Movie Lens dataset was constructed. The optimal model incorporated the effects of both user and movie bias were incorporated in the model, and these valiables were regulised to incorporate movies will a low number of ratings.

The aim of the project was to develop an algorithm lower than 0.87750, which was achieved by the Movie and User Effects and Regularised Movie and User Effects model.