HarvardX Data Science Capstone: MovieLens Project

Medea

5/3/2021

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1 Introduction

In our modern era business success often depends if we are able to recommend correct product to the end-user. The good example of this is streaming services like Netflix. To keep users engaged we must provide them relative content.

In this project we pursued two simple objectives:

1. Try to analyze what were the key factors that contributed to the high or low rating for the specific user, which is the the heart of movie recommendation
2. Make RMSE < 0.86490 (We have built our movie rating predictation model by expanded what we have learned in Prof. Rafael A Irizarry's class about Netflix challenge, Assumptions here reader is familiar terms like RMSE & regularization, so we won't need to redefine them. We would highly recommend to check his "Introduction to Data Science".)

Data we used in the analysis comes from GroupLens, 10M version, which makes our work simpler but is sufficient to draw vital conclusions. We performed data wrangling: split data for training/testing/validation reasons, compare different biases and achieve our goals.

2 Analysis

After download data we have reviewed columns of the movielens, we decided to extract year from timestamp as separate column. For analysis data was split into edx (90%) & validation(10%) sets . Former for training and latter for the final validation.

We observed columns/dimensions and distinct users, movies, genres, year in the edx/validation dataset

```r
colnames(edx)
```

```
## [1] "userId"    "movieId"   "rating"    "timestamp" "title"     "genres"
## [7] "year"
```

```r
dim(edx)
```

```
## [1] 9000055       7
```

```r
dim(validation)
```

```
## [1] 999999      7
```

```r
edx %>%
  summarize(n_users = n_distinct(userId),
            n_movies = n_distinct(movieId),
            n_genres=n_distinct(genres),
            n_year=n_distinct(year),
            )
```

```
##   n_users n_movies n_genres n_year
## 1   69878    10677      797     15
```

Based on intuition movie itself as well as crankiness of the user contributes overall rating of the movie. This can be easily proved by data. We also review other possible bias factors. So questions we've tried to answer:

1. What RMSE we will get if we use naive approach, e.i. if we follow our intuition and give movies rating as average of whole ratings
2. What if we only consider movie affect?
3. What if we only consider user affect?
4. What if we only consider year affect?
5. What if we only consider genres affect?
6. What if we use different combination of those?
7. Should we consider using of regularization?

To create reliable model we divide edx dataset into the train(90%) and test(10%) sets. We also make sure userId and movieId in test_set are also in train set

```r
test_index_edx <- createDataPartition(y = edx$rating, times = 1, p = 0.1, list = FALSE)
train_set <- edx[-test_index_edx,]
tmp_test_set <- edx[test_index_edx,]

# Ensure userId and movieId in test_set are also in edx set
test_set <- tmp_test_set %>%
  semi_join(train_set, by = "movieId") %>%
  semi_join(train_set, by = "userId")

# Add rows removed from test set back into train set
removed_test <- anti_join(tmp_test_set, test_set)
```

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

```
train_set <- rbind(train_set, removed_test)
```

First let's develop simple model and predict the same rating for all movies regardless of user. Here all the differences explained by random variation and model would look like this:

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

Which is translated into following code:

```
#Naive rmse model
mu <- mean(train_set$rating)
naive_rmse <- RMSE(test_set$rating, mu)
naive_rmse
```

```
## [1] 1.061135
```

```
rmse_results <- tibble(method = "Average", RMSE = naive_rmse)
```

Once we have a starting line model we can start to augment it. For example let's consider movie effect only. It can be depicted using following formula:

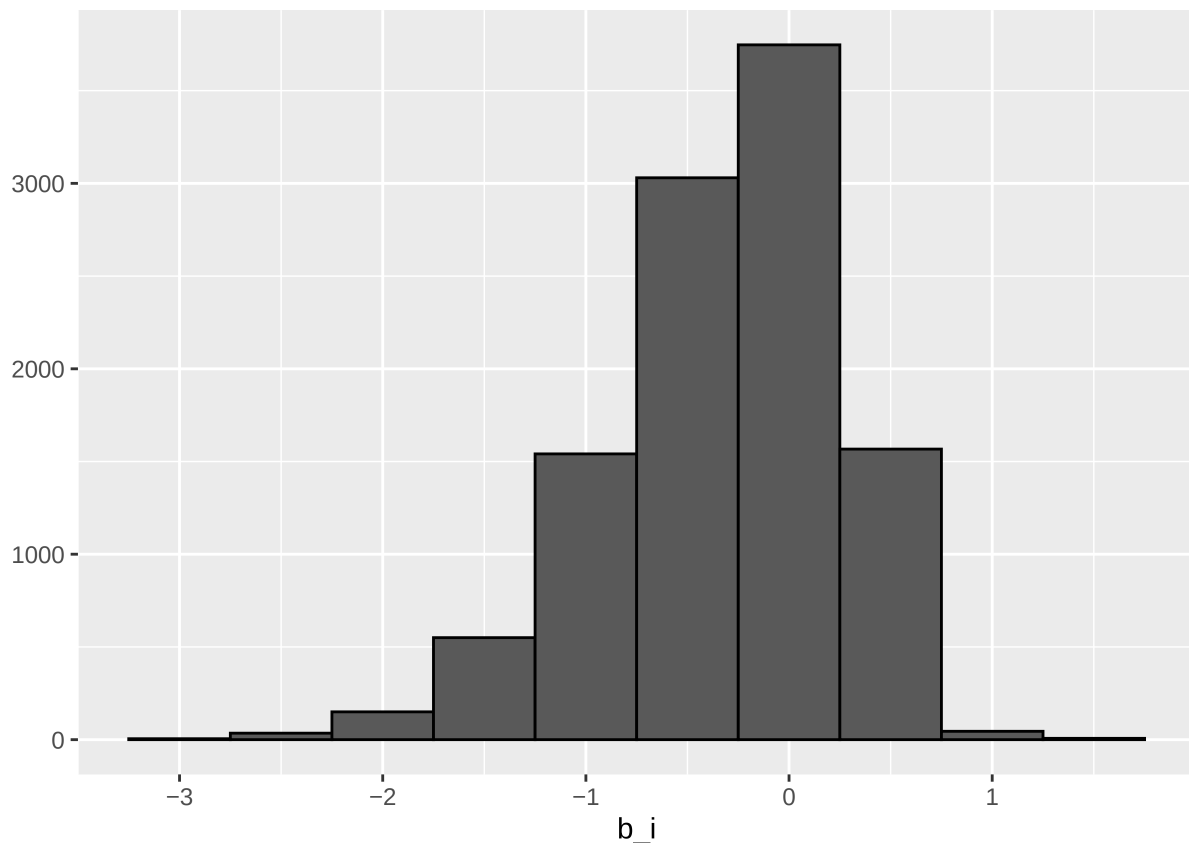
$$Y_{u,i} = \mu + b_i + \varepsilon_{u,i}$$

where term b_i to represent average ranking for movie.

```
#Predict using only movie effect
movie_avgs <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu))

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

i_rmse <-RMSE(predicted_ratings, test_set$rating)
i_rmse
```

```
## [1] 0.9441568
```

```
rmse_results <- rmse_results %>% add_row(method = "Movie", RMSE = i_rmse)
qplot(b_i, data = movie_avgs, bins = 10, color = I("black"))
```



The result we get is better than naive one. Although we've proceed with checking other possible biases, but for simplicity reasons here we are omitting the discussion the most of the scenarios and focus on the two which have given us the best results: Movie/User/Year/Genres and Movie/User/Year/Genres/Regularization.

Movie/User/Year/Genres combination can be described using following formula:

$$Y_{u,i} = \mu + b_i + b_u + b_y + b_g + \varepsilon_{u,i}$$

```
#Predict using user & movie & year & genres effect
genres_avgs <- train_set %>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  left_join(year_avgs, by='year') %>%
  group_by(genres) %>%
  summarize(b_g = mean(rating - mu - b_i - b_u - b_y))

predicted_ratings <- test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  left_join(year_avgs, by='year') %>%
  left_join(genres_avgs, by='genres') %>%
  mutate(pred = mu + b_i + b_u + b_y + b_g) %>%
  pull(pred)

i_u_y_g_rmse<-RMSE(predicted_ratings, test_set$rating)
rmse_results <- rmse_results %>% add_row(method = "Movie/User/Year/Genres",
                                         RMSE = i_u_y_g_rmse)
i_u_y_g_rmse
```

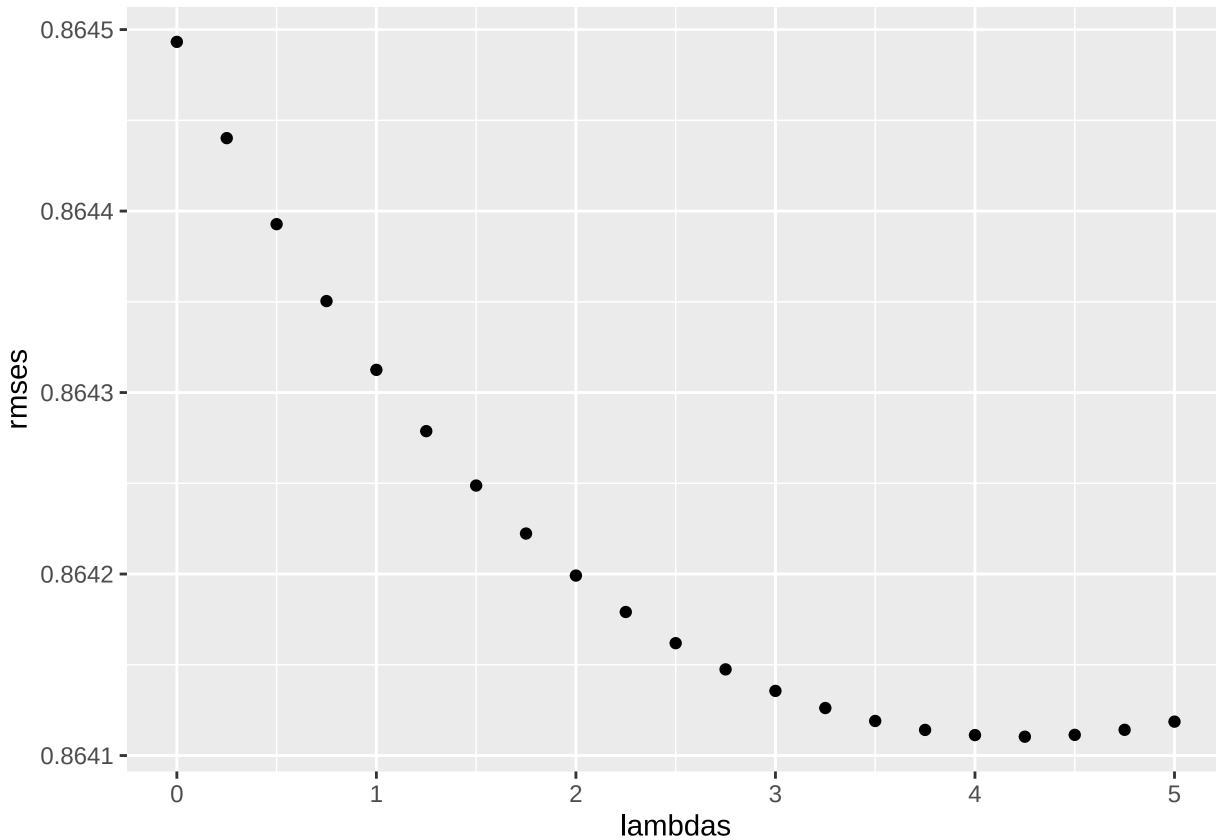
```
## [1] 0.865588
```

Result is good but we still have not reached our second objective. e.i. RMSE < 0.86490. From the edx dataset is easy to see that some movies are receiving only a handful reviews and their rating could mess up with recommendation. To mitigate this effect regularization should be performed and suitable lambda which minimizes RMSE be chosen.

```
mu <- mean(train_set$rating)
lambdas <- seq(0, 5, 0.25)
rmses <- sapply(lambdas, function(lambda) {
  # Calculate the average by user

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

  # Calculate the average by user

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

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

  b_g <- train_set %>%
    left_join(b_i, by='movieId') %>%
    left_join(b_u, by='userId') %>%
    left_join(b_y, by='year') %>%
    group_by(genres) %>%
    summarize(b_g = mean(rating - mu - b_i - b_u - b_y))

  # Compute the predicted ratings on test_set dataset

  predicted_ratings <- test_set %>%
    left_join(b_i, by='movieId') %>%
    left_join(b_u, by='userId') %>%
    left_join(b_y, by='year') %>%
    left_join(b_g, by='genres') %>%
    mutate(pred = mu + b_i + b_u + b_y + b_g) %>%
    pull(pred)

  # Predict the RMSE on the validation set

  return (RMSE(predicted_ratings,test_set$rating))
})
min_lambda <- lambdas[which.min(rmses)]
```

```r
i_u_y_g_cv_rmse<-min(rmses)
rmse_results <- rmse_results %>% add_row(method = "Movie/User/Year/Genres cross-validation",
                                         RMSE = i_u_y_g_cv_rmse)
```

Let's plot our lambdas to observe dynamic



3 Results

After observing results we had from our training set we conclude that the most valuable bias combination is : user/movie/year/genre in combination with data regularization, the most insignificant effect is Year, but we still decide to keep it. Lambda value used:

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

The results on train set

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

method	RMSE
Average	1.0611350
Movie	0.9441568
User	0.9795916

method	RMSE
Year	1.0593807
Movie/User	0.8659736
Movie/User/Year	0.8659598
Movie/User/Genres	0.8656018
Movie/User/Year/Genres	0.8655880
Movie/User/Year/Genres cross-validation	0.8641104

Once we tried different combinations of bias and created our final model we test it against validation set.

So we have achieved our objectives.

4 Conclusion

Next step in analyzes is to split "genres" column into separate columns and see if some genres combination contributes rating more than others. With current data Also it is unfortunate that last year in data is 2009, since it would be interesting to see how global pandemic affected movie ratings and if now year changed from insignificant parameter to something very important.