Harvard PH125.9x Capstone: MovieLens Analysis

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Introduction/Overview/Executive Summary

The goal of this project is to develop an algorithm to predict movie ratings.

This analysis is performed on (MovieLens) dataset. It contains 10 millions ratings and 100 000 tags applications applied to 10 000 movies by 72 000 users.

After downloading the entire dataset, two dataframes are created:

- `edx` which is used to perform the analysis and develop the algorithm to predict ratings
- `validation` which contains the true values of the predictions

The original datasets provided by the exercise are:

Table 1: Default summary for edx dataframe

	Length	Class	Mode
userId	9000055	-none-	numeric
movieId	9000055	-none-	numeric
rating	9000055	-none-	numeric
timestamp	9000055	-none-	numeric
title	9000055	-none-	character
genres	9000055	-none-	character

Table 2: Default summary for validation dataframe

	Length	Class	Mode
userId	999999	-none-	numeric
movieId	999999	-none-	numeric
rating	999999	-none-	numeric
timestamp	999999	-none-	numeric
title	999999	-none-	character
genres	999999	-none-	character

Table 3: Head of edx dataframe

	userId	movieId	rating	timestamp	title	genres
1	1	122	5	838985046	Boomerang (1992)	Comedy|Romance
2	1	185	5	838983525	Net, The (1995)	Action|Crime|Thriller
4	1	292	5	838983421	Outbreak (1995)	Action|Drama|Sci-Fi|Thriller
5	1	316	5	838983392	Stargate (1994)	Action|Adventure|Sci-Fi
6	1	329	5	838983392	Star Trek: Generations (1994)	Action|Adventure|Drama|Sci-Fi
7	1	355	5	838984474	Flintstones, The (1994)	Children|Comedy|Fantasy

Table 4: Summary of edx dataframe

userId	movieId	rating	timestamp	title	genres
Min. : 1	Min. : 1	Min. :0.500	Min. :7.897e+08	Length:9000055	Length:9000055
1st Qu.:18124	1st Qu.: 648	1st Qu.:3.000	1st Qu.:9.468e+08	Class :character	Class :character
Median :35738	Median : 1834	Median :4.000	Median :1.035e+09	Mode :character	Mode :character
Mean :35870	Mean : 4122	Mean :3.512	Mean :1.033e+09	NA	NA
3rd Qu.:53607	3rd Qu.: 3626	3rd Qu.:4.000	3rd Qu.:1.127e+09	NA	NA
Max. :71567	Max. :65133	Max. :5.000	Max. :1.231e+09	NA	NA

The greatest challenge in analysing these data is their volume. The most of the built-in models distributed via caret will simply run out of memory.

This dataset was already used for a test regarding date parsing in the module HarvardX: PH125.6x Data Science: Wrangling. The module HarvardX: PH125.8x Data Science: Machine Learning illustrated two important concept using this dataset:

- Recommendation systems: use ratings that users have already given to some items in order to make specific recommandations
- Regularization: add information in order to solve an ill-posed problem or to prevent overfitting

The key steps required to identify an optimal solution are:

- prepare the data for the analysis (normalize some columns, extract new features to prepare the analysis)
- create a train and a test set partition out of `edx` dataset to start and validate the analysis
- ~explore the content of `train_set` and visualize the distribution of the outcome (`rating`) by every feature~
- ~use `train_set` implement several prediction models (see Method/Analysis section for details)~
- ~run models and ensembles against `test_set`~
- ~evaluate the accuracy and the RMSE of each solution based on `test_set` (see Result for the output)~
- develop a linear model on `edx` after exploring its content and validate the predictions against the actual rating
- perform cross validation on the choosen model to ensure an optimal tuning
- report the RMSE against the true values to complete the exercise (RMSE < 0.86490 required)

The quality of the prediction is evaluated using the root mean squared error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_i (\hat{y}_i - y_i)^2}$$

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

Method/Analysis

The process of this analysis includes data wrangling, data exploration and the description of the modeling approach.

Data Wrangling/Cleaning

The `edx` and `validation` are the result of some manipulation on a downloaded dataset from `grouplens.org`.

1. download the zip file in a temporary directory and unzip it into the workspace directory
2. read the raw data from two `.dat` files creating `ratings` and `movies` dataframes
3. normalize column names and cast value as `numeric` and `character`, then join both datasets into the `movielens` dataframe
4. partition the data in `movielens` to create a train test used for developing the model (`edx`, 90%) and the true values used to calculate the RMSE of the final model (`validation`, 10%)
5. ensure that userId and movieId in validation set are also in edx set

```r
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")

# 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 <- 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")

# 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,]

# 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)
```

Before starting the analysis, we are going to prepare the data for the analysis:

```
wrangle_data <-function(ds) {
  ds %>%
    mutate(
      userId = factor(userId), # int to factor
      movieId = factor(movieId), # num to factor
      datetime = as_datetime(timestamp), # parse int into date
      movieYear = str_sub(title,-5,-2), # extract movieYear from title (xxxx),
      reviewYear = factor(year(datetime)),
      reviewWeek = factor(week(datetime))
    )
}
```

Instead of using all the known observations from `edx` dataset, we create a `train_set` and a `test_set` to continue this analysis as follows:

```
set.seed(17, sample.kind="Rounding")
test_index <- createDataPartition(y = edx$rating, times = 1, p = 0.1, list = FALSE)
train_set <- edx[-test_index,]
temp <- edx[test_index,]

# Ensure that userId and movieId in the test_set are included in the train_set
test_set <- temp %>%
  semi_join(train_set, by = "movieId") %>%
  semi_join(train_set, by = "userId")

removed <- anti_join(temp, test_set)
train_set <- rbind(train_set, removed)

rm(test_index, temp, removed)
```

We perform our analysis unsing `train_set` and we validate it with `test_set`.

Data Exploration and Insights

> After a first exploration exploration of the most common ML algorithms, we realized that the `train_set` was too large to be trained on my machine. The final model implementation will provide predictions on `edx` which may be compared to the actual `edx$rating`. For this reason the data exploration will be done on `edx` and the `train_set - test_set` won't be used in this analysis.

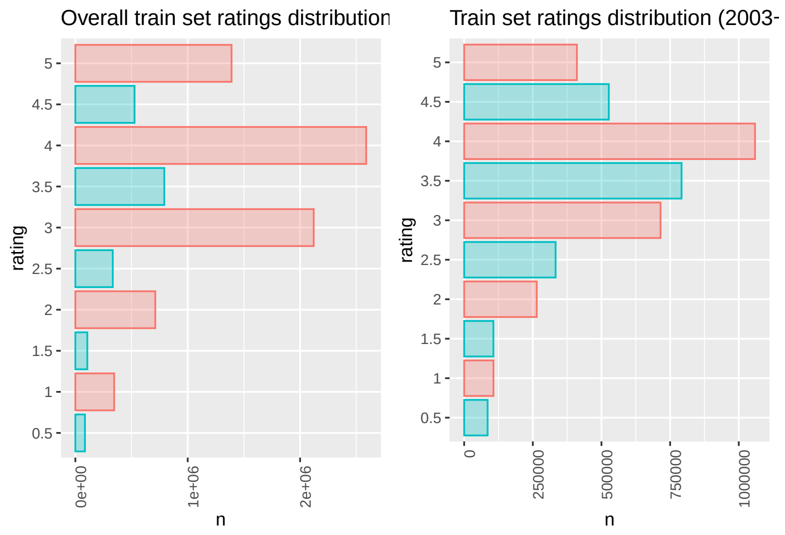
The features we may use in our analysis:

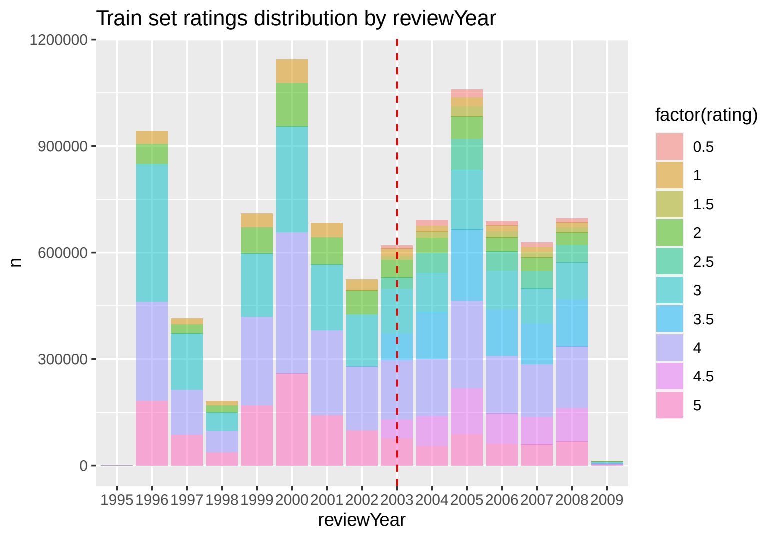
```r
setdiff(colnames(edx), c("rating", "title", "timestamp"))
```

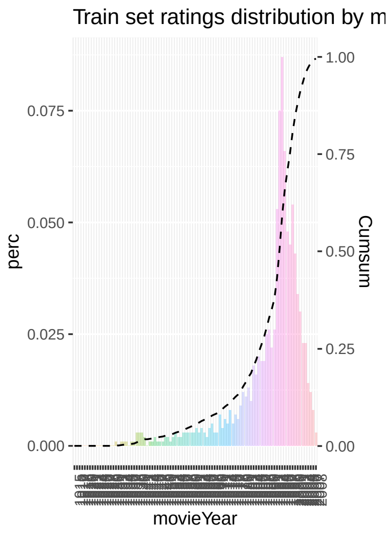
```
## [1] "userId"     "movieId"    "genres"     "datetime"   "movieYear"
## [6] "reviewYear" "reviewWeek"
```

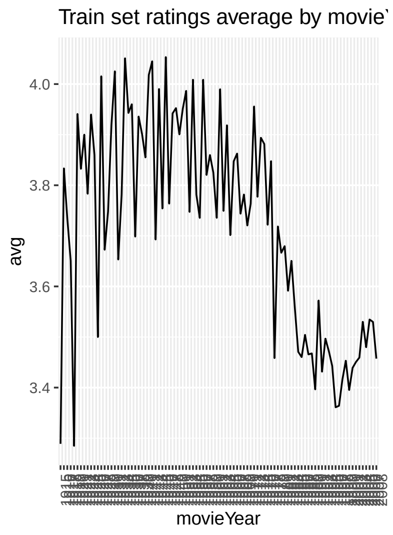
Since our goal is to predict ratings, we start looking at the overall ratings distribution in the `edx` dataset.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.500   3.000   4.000   3.512   4.000   5.000
```





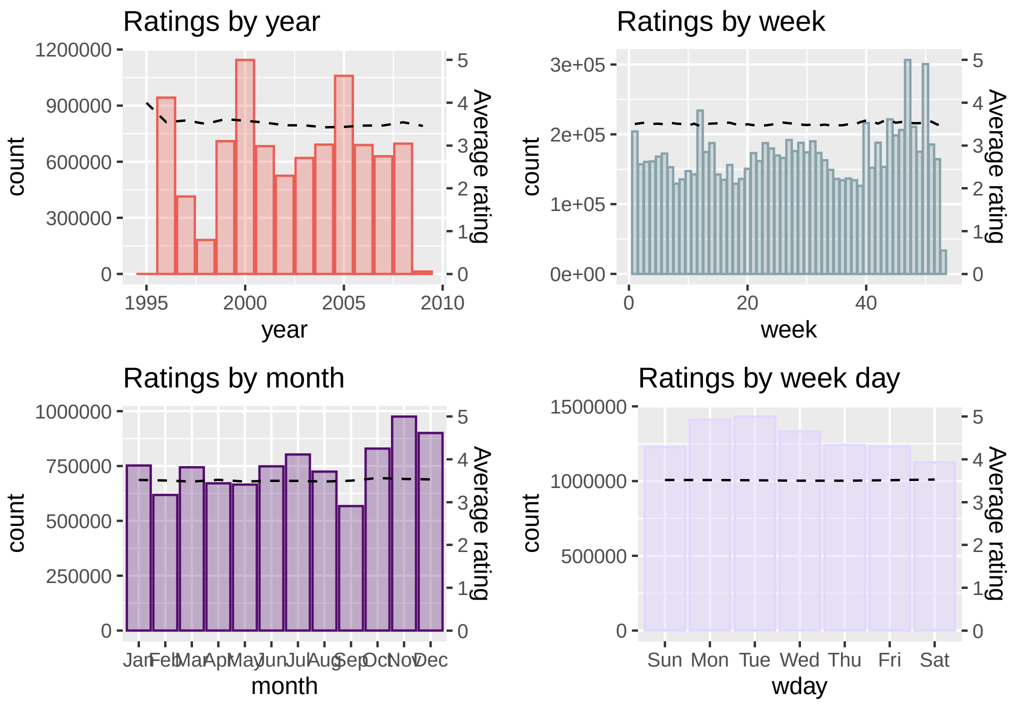




```
##    movieYear              avg
##  Length:94          Min.   :3.285
##  Class :character   1st Qu.:3.511
##  Mode  :character   Median :3.748
##                     Mean   :3.721
##                     3rd Qu.:3.900
##                     Max.   :4.053
```

We notice that whole star ratings are predominant compares to half star rating. One reason to explain the importance of this difference is that half star ratings have been introduced in 2003. We can also see that a movie is more likely to receive a rating if it was shot between the early 90s and 2000s. On average, movies before the 80s tend to have an higher rating.

Breaking down the distribution by the review `timestamp`, even if the rating count varies somehow over the time, the average rating seems quite constant.

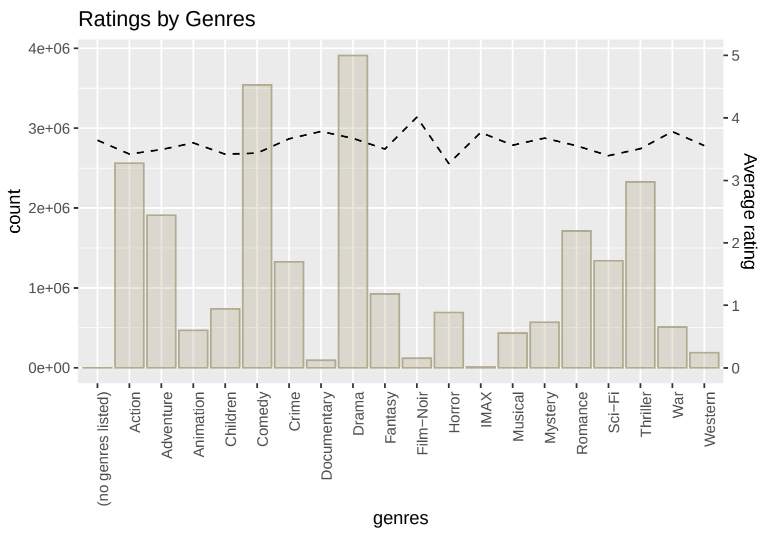


We can clearly see that on average ratings is costant across the `month` and the `wday`. There is some seasonality in the reviews distribution, with a majority of ratings given in the last quarter of the year.

The ratings breakdown by top 10 `genres` is:

Table 5: Top rated movie genres

genres	count	avg
Drama	3910127	3.673131
Comedy	3540930	3.436908
Action	2560545	3.421405
Thriller	2325899	3.507676
Adventure	1908892	3.493544
Romance	1712100	3.553813
Sci-Fi	1341183	3.395743
Crime	1327715	3.665925
Fantasy	925637	3.501946
Children	737994	3.418715



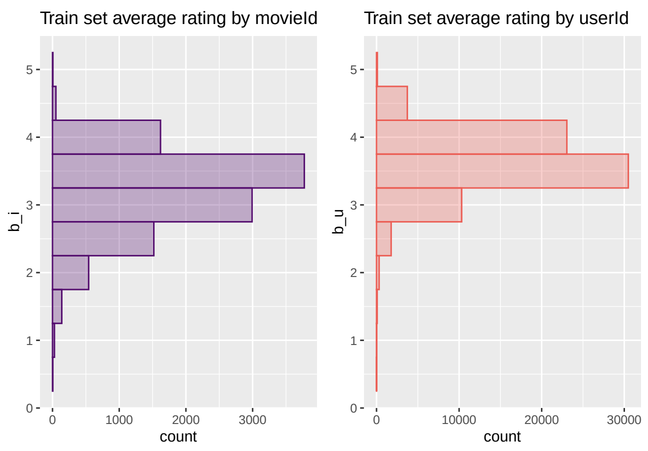
Comparing the distribution of rating by `movieId` and by `userId`

```r
n_distinct(edx$movieId)
```

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

```r
n_distinct(edx$userId)
```

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



Out of curiosity, the 10 most rated movies are:

Table 6: Top rated movies

movieId	title	count	avg_rating
296	Pulp Fiction (1994)	31362	4.154789
356	Forrest Gump (1994)	31079	4.012822
593	Silence of the Lambs, The (1991)	30382	4.204101
480	Jurassic Park (1993)	29360	3.663522
318	Shawshank Redemption, The (1994)	28015	4.455131
110	Braveheart (1995)	26212	4.081852
457	Fugitive, The (1993)	25998	4.009155
589	Terminator 2: Judgment Day (1991)	25984	3.927859
260	Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977)	25672	4.221311
150	Apollo 13 (1995)	24284	3.885789

This data exploration has been done within the limits of my machine capacity More powerful machines can help to find out more advanced patterns.

Modeling

In the first data exploration we could not find identify a single feature allowing to predict clearly.

As I first step we tried to solve the problem as a `classification` problem with the following outcomes:

```
seq(0.5, 5, 0.5)
```

```
##  [1] 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
```

With this result normalization, every result could have been converted to the real values levels:

```
n <- 2.7
ceiling(n*2)/2
```

In *HarvardX: PH125.8x* we have seen that if we want to handle more than two features we can use regression trees or random forrest.

Running a regression tree on all these dimensions was not really helpful:

```r
# Regression tree model
rt_model <- rpart(rating ~ ., data = train_set)
plot(rt_model, margin = 0.1)
text(rt_model, cex = 0.75)

# Warning message:
# In labels.rpart(x, minlength = minlength) :
#   more than 52 levels in a predicting factor, truncated for printout
```

Other approaches like randomForrest will just run out of memory.

Models such as logistic_regression, lda, qda, loess, knn perform better with at maximum two features. We may just elect two features or use principal component analysis to define two features.

In this report we are modeling the solution taking inspiration from the approach suggested by the team winning the Netflix $1 million award in 2009.

The solution suggested was based on two models:

a. Normalization of global effects

- consider a baseline rating (overall mean)
- a user specific effect based on the previous ratings
- a movie specific effect based on the previous ratings
- a specific interaction (e.g. I like this movie because a given actor is playing)

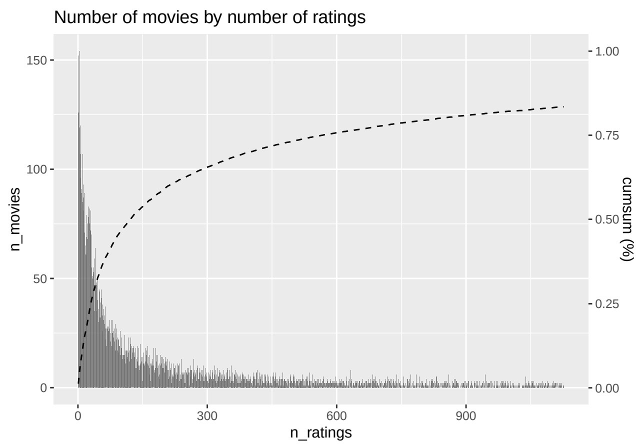
b. Neighborhood Models

- item-item approach: similar items may receive similar ratings
- user-user approach: similar users may give similar ratings

In our model we are going to regularize the data using *penalized least square* to constraint the total variability of the effect sizes.

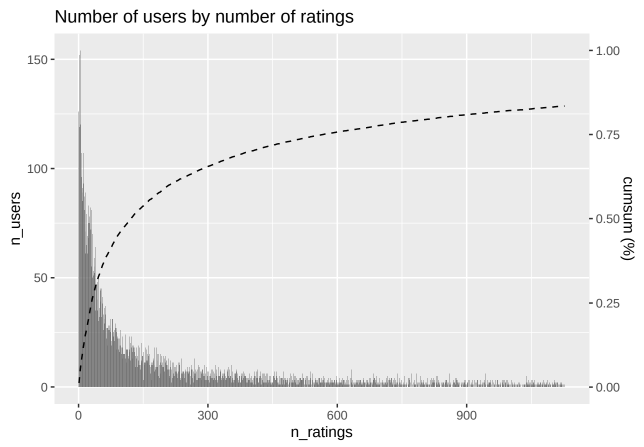
As we can see most of the items have very few ratings:

```r
movies_reviews_count <- edx %>% group_by(movieId) %>% count() %>% as_tibble() %>%
  group_by(n) %>% count() %>% rename(n_ratings=n, n_movies=nn)
movies_reviews_count <- movies_reviews_count %>%
  add_column(cumsum=cumsum(movies_reviews_count$n_movies/sum(movies_reviews_count$n_movies)))

movies_reviews_count %>% head(1000) %>%
  ggplot(aes(x=n_ratings)) +
  geom_histogram(aes(y = n_movies), stat = "identity", alpha = 0.7) +
  geom_line(aes(y=cumsum * max(movies_reviews_count$n_movies)), linetype = "dashed") +
  scale_y_continuous(sec.axis = sec_axis(~./max(movies_reviews_count$n_movies), name = "cumsum (%)")) +
  ggtitle("Number of movies by number of ratings")
```



```r
rm(movies_reviews_count)
```

```r
users_reviews_count <- edx %>% group_by(movieId) %>% count() %>% as_tibble() %>%
  group_by(n) %>% count() %>% rename(n_ratings=n, n_users=nn)
users_reviews_count <- users_reviews_count %>%
  add_column(cumsum=cumsum(users_reviews_count$n_users/sum(users_reviews_count$n_users)))

users_reviews_count %>% head(1000) %>%
  ggplot(aes(x=n_ratings)) +
  geom_histogram(aes(y = n_users), stat = "identity", alpha = 0.7) +
  geom_line(aes(y=cumsum * max(users_reviews_count$n_users)), linetype = "dashed") +
  scale_y_continuous(sec.axis = sec_axis(~./max(users_reviews_count$n_users), name = "cumsum (%)")) +
  ggtitle("Number of users by number of ratings")
```



```r
rm(users_reviews_count)
```

In order to identify the `lambda` parameter (penalty term) to apply to our model, we are going to use the `test_set` we extracted earlier.

> It is important to note that all users and movies in `validation` are included by design in the `edx`. This allows us to stretch the impact of the section b. of the winning algorithm introduced above.

To identify an acceptable solution (RMSE < 0.86490), we first define the `RMSE` function:

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

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

1. naive approach: use the average

A first naive approach could be just to take the average rating and predict all the results with it:

```
predict_model_0 <- function(df, l=0) {
  rep(mu, nrow(df))
}

# Rudimental model execution timing for benchmarks
start_time <- Sys.time()
preds_0 <- predict_model_0(edx)
model_0_rmse <- RMSE(y, preds_0)
end_time <- Sys.time()
model_0_time <- end_time - start_time
rmse_results <- tibble(method = "Model 0: Average", RMSE = model_0_rmse, accuracy = mean(preds_0==y), la

rm(preds_0, start_time, end_time, model_0_time)
```

2. Introduce the movie effect

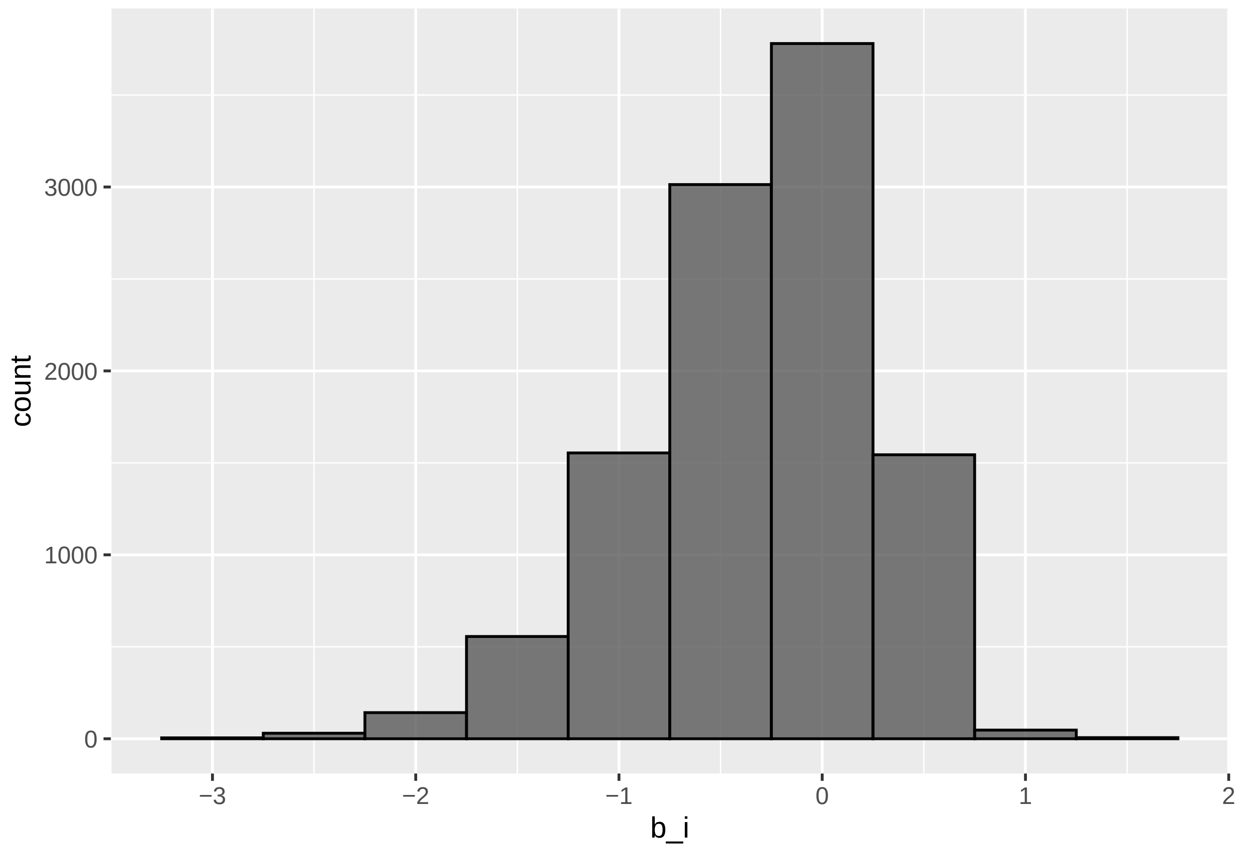
```
# fit <- lm(rating ~ movieId, data = train_set)
# Error: vector memory exhausted (limit reached?)
```

On a regular machine is not possible to train a linear model on by `movieId`. There are two options:

- reduce the size of the `train_set`
- avoid using some vendor library and write the model by ourselves

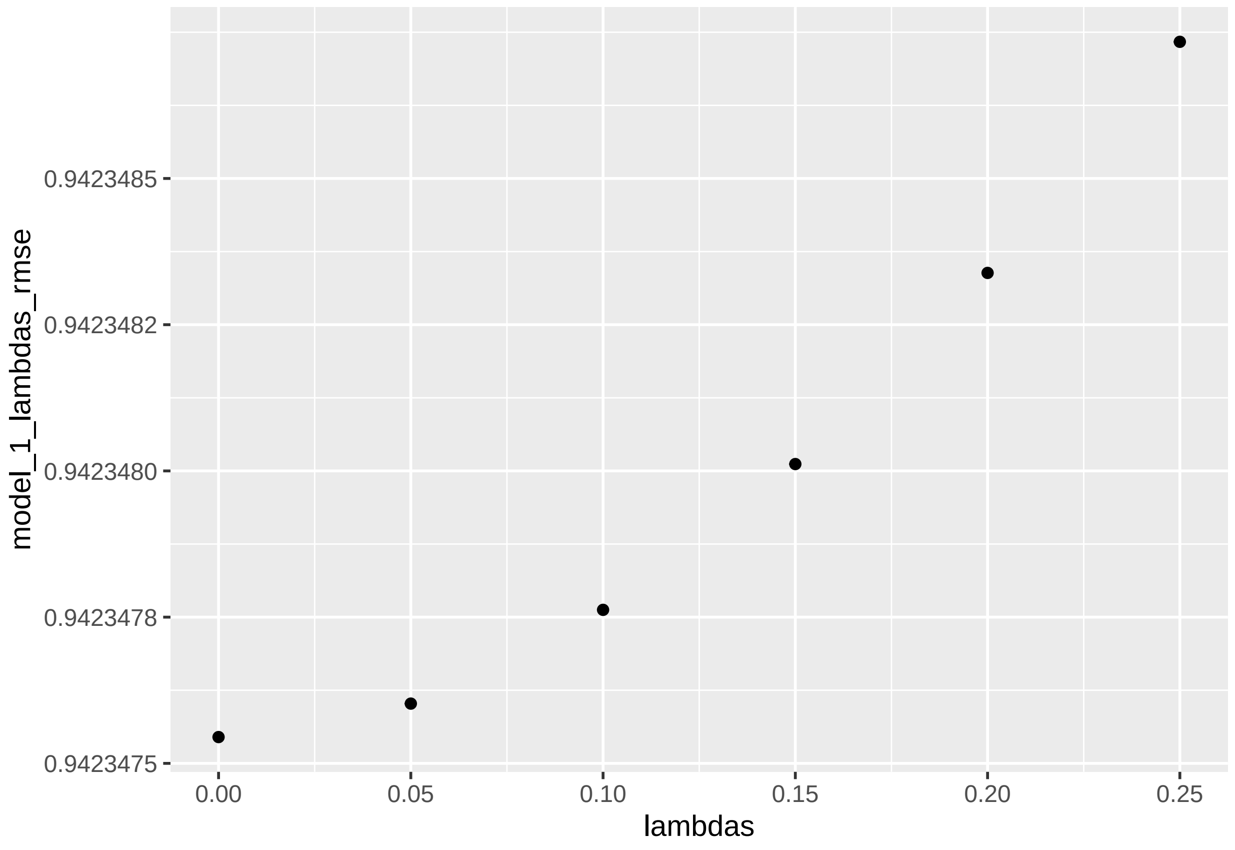
Following the second approach:

```
# regularized movie averages
l <- 0
reg_movie_avgs <- edx %>%
     group_by(movieId) %>%
     summarize(b_i = sum(rating - mu)/(n()+l))

ggplot(aes(x=b_i), data=reg_movie_avgs) + geom_histogram(bins=10, alpha=0.8, color="black")
```



```
predict_model_1 <- function(df, l=0) {
  mu <- mean(edx$rating)
  reg_movie_avgs <- edx %>%
     group_by(movieId) %>%
     summarize(b_i = sum(rating - mu)/(n()+l))

  mu + df %>% left_join(reg_movie_avgs, by='movieId') %>% .$b_i
}

# Rudimental model execution timing for benchmarks
start_time <- Sys.time()
preds_1 <-predict_model_1(edx)
model_1_rmse <- RMSE(y, preds_1)
end_time <- Sys.time()
model_1_time <- end_time - start_time

rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Model 1: Movie Effect",
                                     RMSE = model_1_rmse,
                                     accuracy = mean(preds_1==y),
                                     lambda = 0,
                                     time = model_1_time
                                     ))


# Minimize the RMSE using a penalty factor
```

```r
l_min <- 0
l_max <- 5
l_step <- .25
lambdas <- seq(l_min, l_max, l_step)

model_1_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_1(edx, l))
})
l <- lambdas[which.min(model_1_lambdas_rmse)]

l_min <- max(0, l-l_step)
l_max <- l+l_step
l_step <- l_step/5
lambdas <- seq(l_min, l_max, l_step)

model_1_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_1(edx, l))
})
l <- lambdas[which.min(model_1_lambdas_rmse)]
qplot(lambdas, model_1_lambdas_rmse)
```

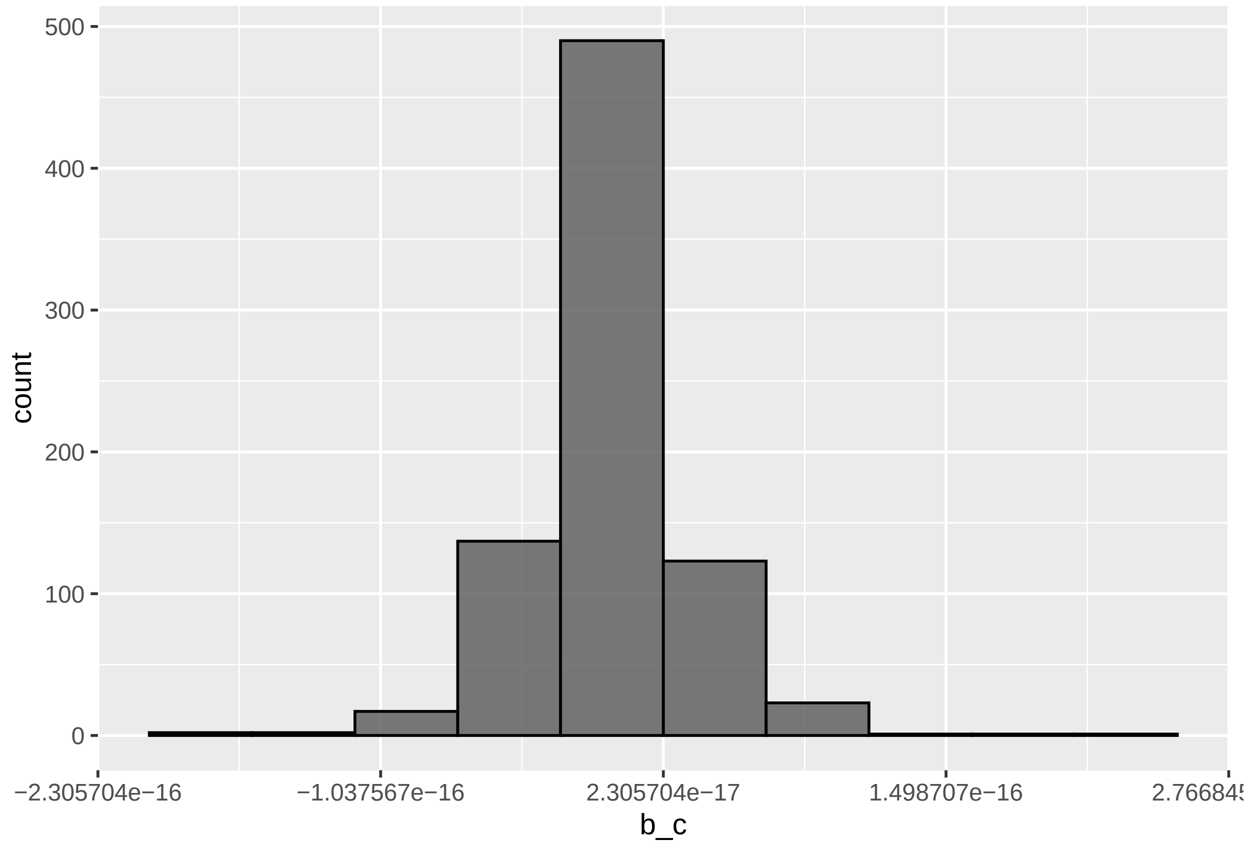


```r
if(l != 0) {
  preds_1l <- predict_model_1(edx, l)
  rmse_results <- bind_rows(rmse_results,
                            data_frame(
                              method="Model 1: Movie Effect (reg)",
                              RMSE = min(model_1_lambdas_rmse),
                              accuracy = mean(preds_1l==y),
                              lambda = l,
                              time = model_1_time
                            ))
}

rm(lambdas, l, l_min, l_max, preds_1, preds_1l, start_time, end_time, model_1_time)
```

3. Introduce the genres effect -> don't

In the model b was described an item-item approach. In order to group similar movies we may used the `genres` column provided in the datasets.

```
## regularized genres averages
reg_genres_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(genres) %>%
    summarize(b_c = mean(rating - mu - b_i))

ggplot(aes(x=b_c), data=reg_genres_avgs) + geom_histogram(bins=10, alpha=0.8, color="black")
```

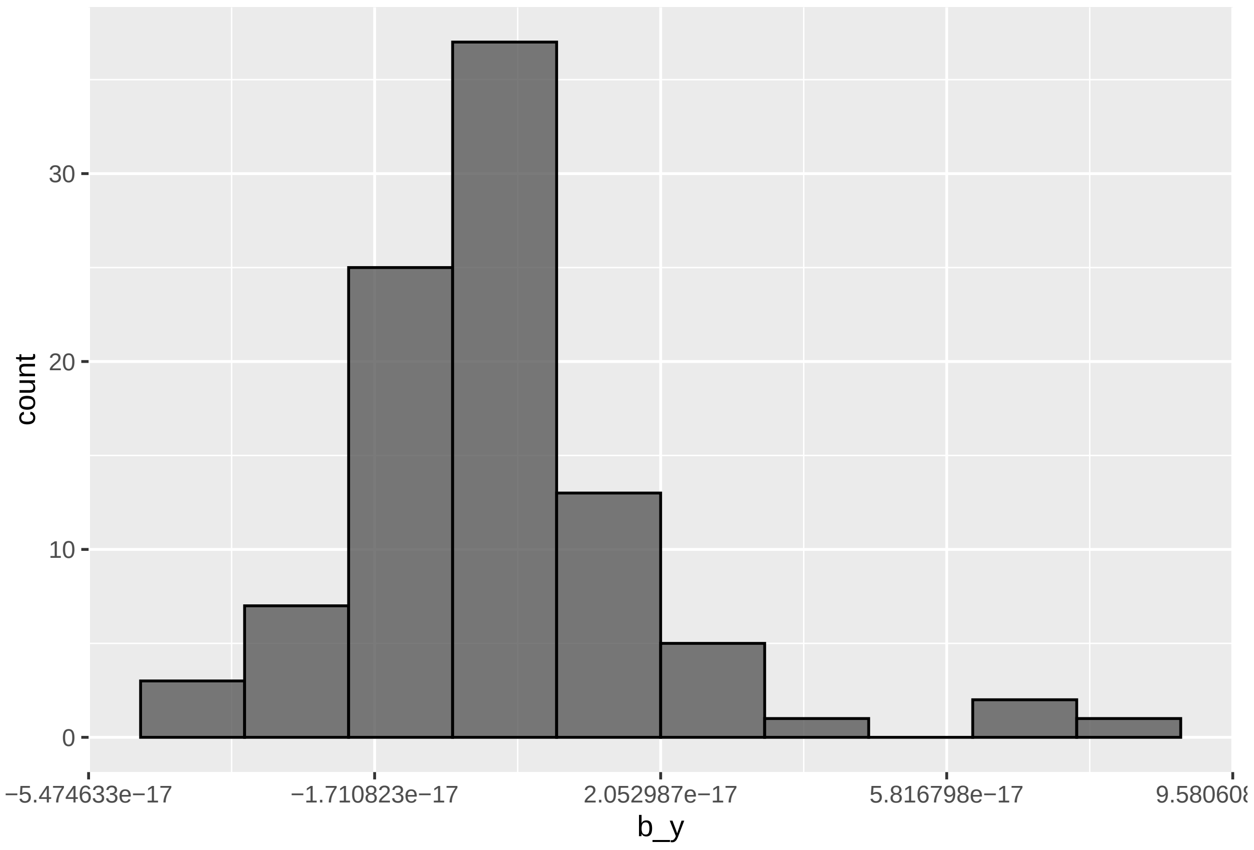


As we can see in the plot, the `genres` effect after the movie effect does not seem to be relevant (affecting the rating only by 10^-17). It is not worth to include it in our model.

4. Introduce the movieYear effect -> don't

Another item-item approach could be explored using `movieYear`.

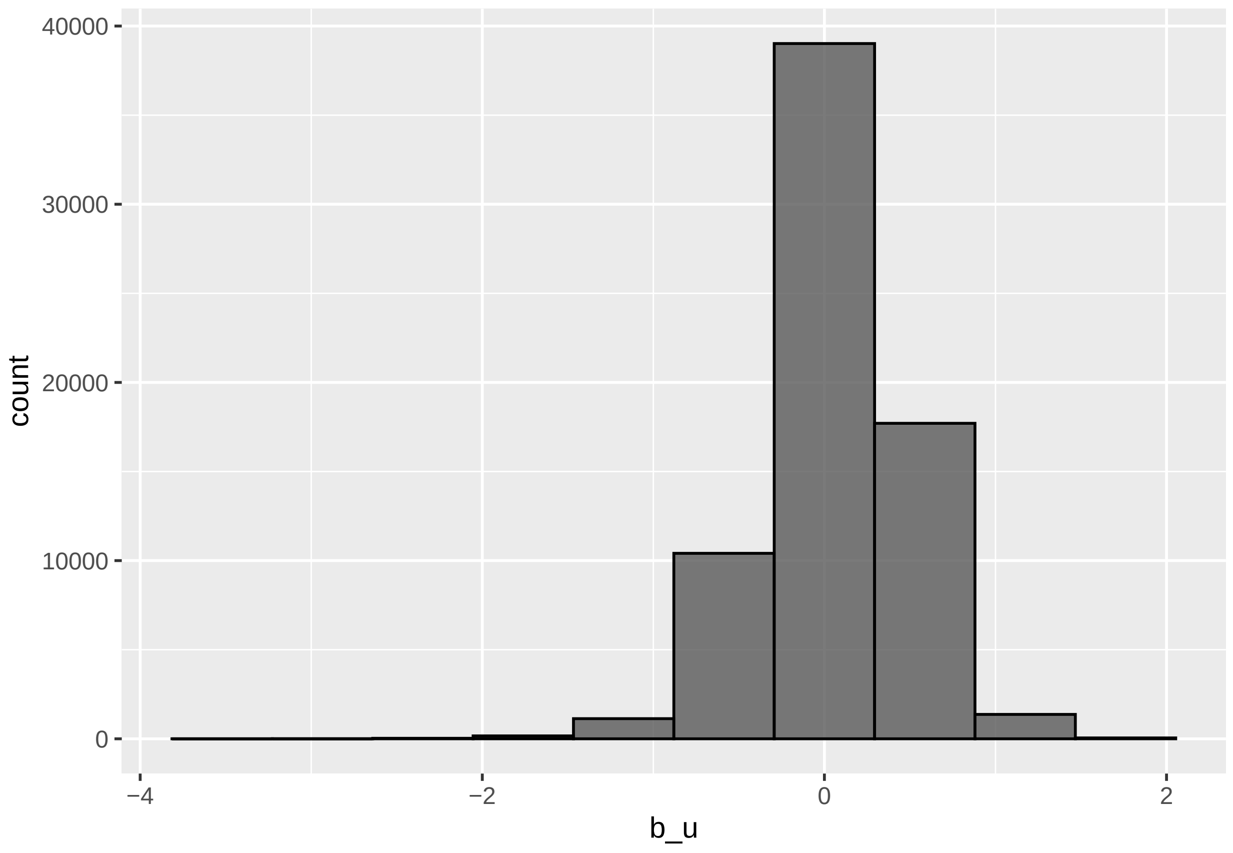
```r
## regularized movieYear averages
reg_movieYear_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(movieYear) %>%
    summarize(b_y = mean(rating - mu - b_i))

ggplot(aes(x=b_y), data=reg_movieYear_avgs) + geom_histogram(bins=10, alpha=0.8, color="black")
```



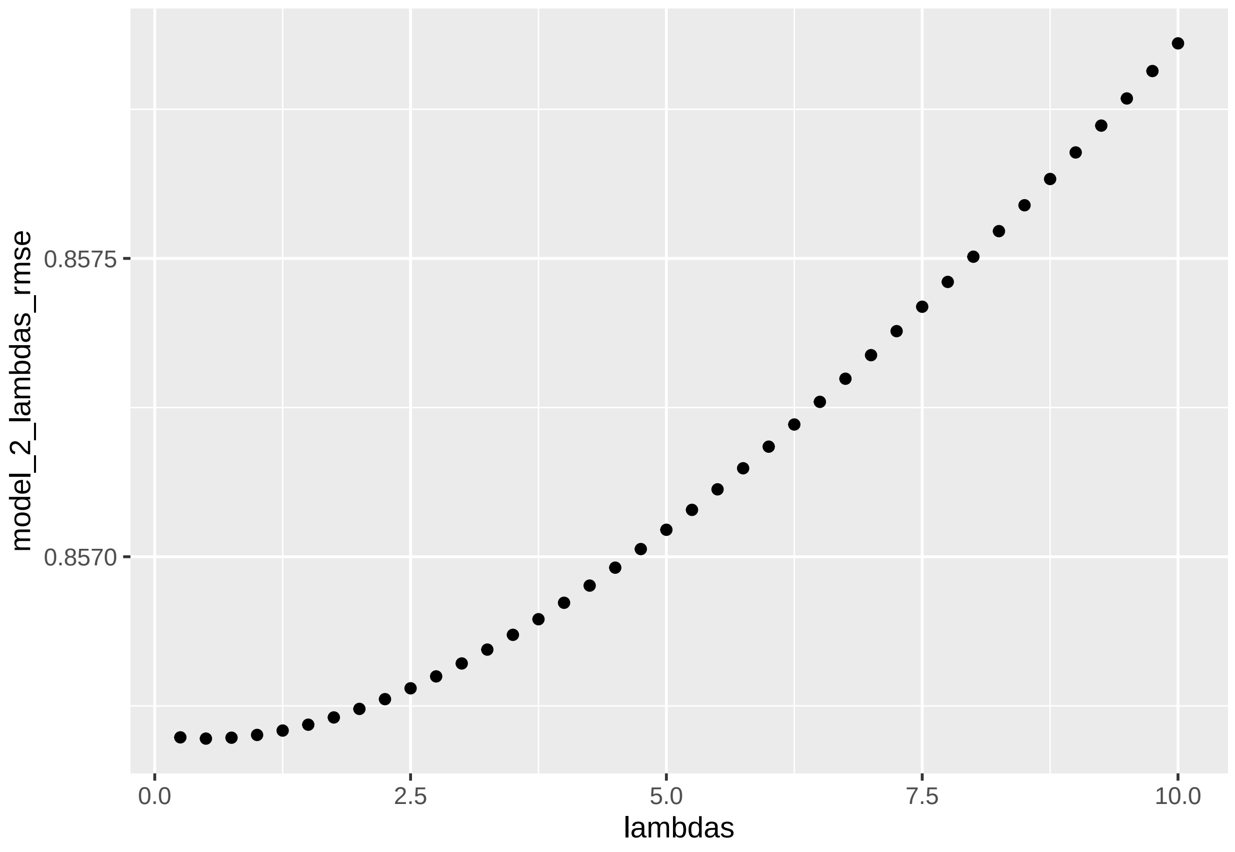
As we can see in the plot, the `movieYear` effect after the movie effect does not seem to be relevant (affecting the rating only by 10^-17). It is not worth to include it in our model.

5. Introduce the userId effect

```r
## regularized reviewYear averages
l <- 0
reg_user_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(userId) %>%
    summarize(b_u = mean(rating - mu - b_i))

ggplot(aes(x=b_u), data=reg_user_avgs) + geom_histogram(bins=10, alpha=0.8, color="black")
```

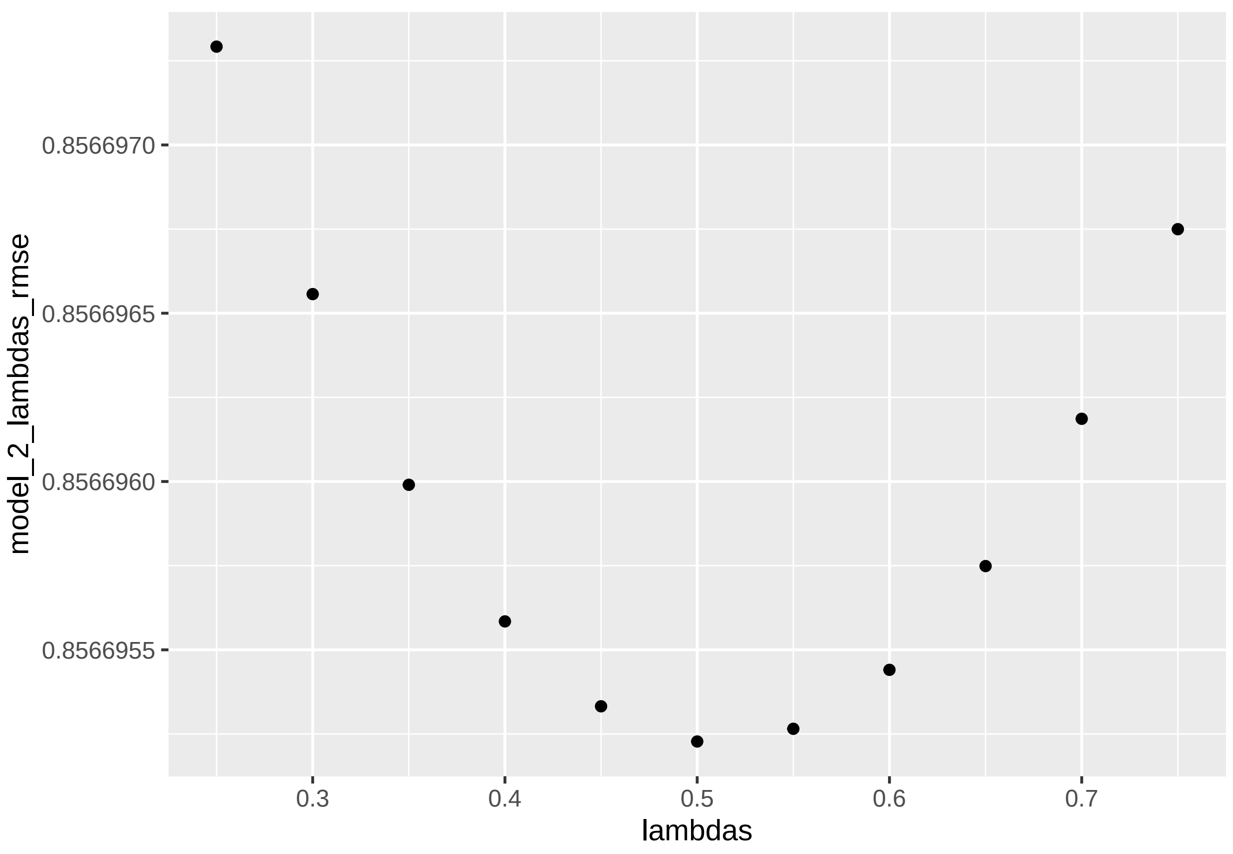


```r
predict_model_2 <- function(df, l=0) {
  mu <- mean(edx$rating)

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

  reg_user_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(userId) %>%
    summarize(b_u = sum(rating - mu - b_i)/(n()+l))

  df %>%
   left_join(reg_movie_avgs, by='movieId') %>%
   left_join(reg_user_avgs, by='userId') %>%
   mutate(pred = mu + b_i + b_u) %>% .$pred
}

# Rudimental model execution timing for benchmarks
start_time <- Sys.time()
model_2_rmse <- RMSE(y, predict_model_2(edx, 0))
end_time <- Sys.time()
model_2_time <- end_time - start_time

preds_2 <- predict_model_2(edx, 0)
rmse_results <- bind_rows(rmse_results,
                                data_frame(method="Model 2: Movie + User Effect",
                                           RMSE = model_2_rmse,
                                           accuracy = mean(preds_2==y),
                                           lambda = 0,
                                           time = model_2_time
                                           ))
# Minimize the RMSE by a penalty factor
l_min <- 0.25
l_max <- 10
l_step <- .25
lambdas <- seq(l_min, l_max, l_step)

model_2_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_2(edx, l))
})
l <- lambdas[which.min(model_2_lambdas_rmse)]
qplot(lambdas, model_2_lambdas_rmse)
```



```
l_min <- max(0, l-l_step)
l_max <- l+l_step
l_step <- l_step/5
lambdas <- seq(l_min, l_max, l_step)

model_2_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_2(edx, l))
})
```

```r
l <- lambdas[which.min(model_2_lambdas_rmse)]
qplot(lambdas, model_2_lambdas_rmse)
```

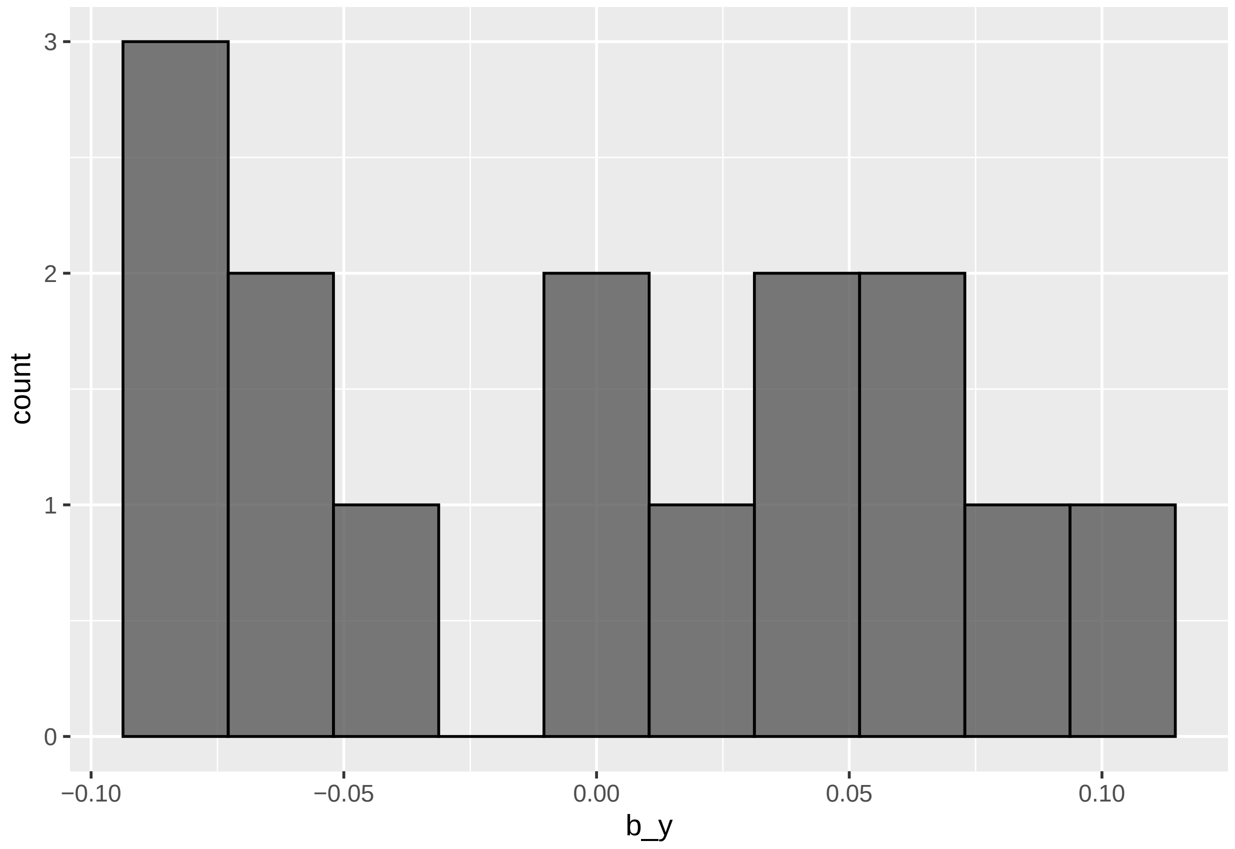


```r
if(l != 0) {
  preds_2l <- predict_model_2(edx, l)
  rmse_results <- bind_rows(rmse_results,
                            data_frame(
                              method="Model 2: Movie + User Effect (reg)",
                              RMSE = min(model_2_lambdas_rmse),
                              accuracy = mean(preds_2l==y),
                              lambda = l,
                              time = model_2_time
                            ))
}
rm(lambdas, L, l_min, l_max, preds_2, preds_2l, start_time, end_time, model_2_time)
```

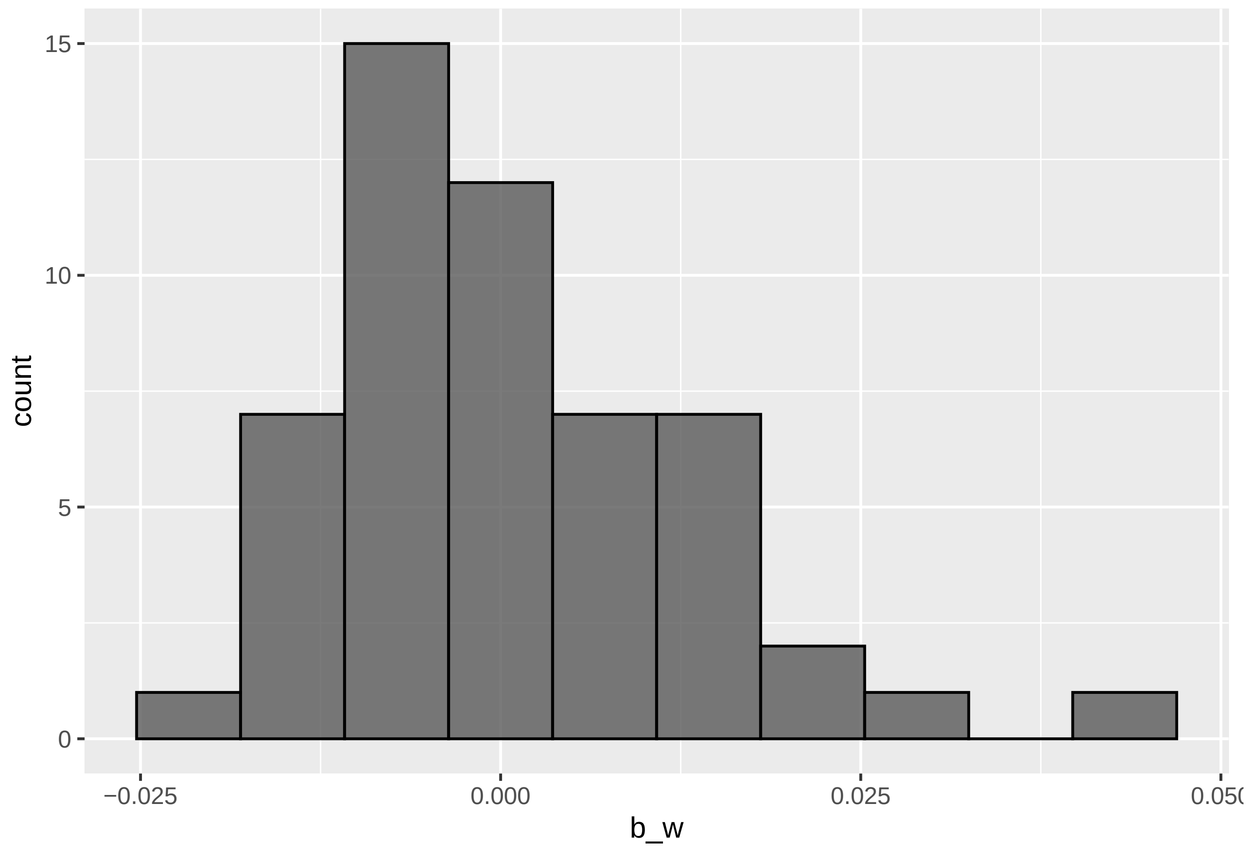
6. Introduce the reviewYear and reviewWeek effect -> don't

We do not have any element to evaluate a user-user approach. On of the few approaches we can imagine is that at a given moment in the time the people tend to rate in a more similar way.

```r
## regularized reviewYear averages
l <- 0
reg_reviewYear_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    left_join(reg_user_avgs, by='userId') %>%
    group_by(reviewYear) %>%
    summarize(b_y = sum(rating - mu - b_i)/(n()+1))

ggplot(aes(x=b_y), data=reg_reviewYear_avgs) + geom_histogram(bins=10, alpha=0.8, color="black")
```

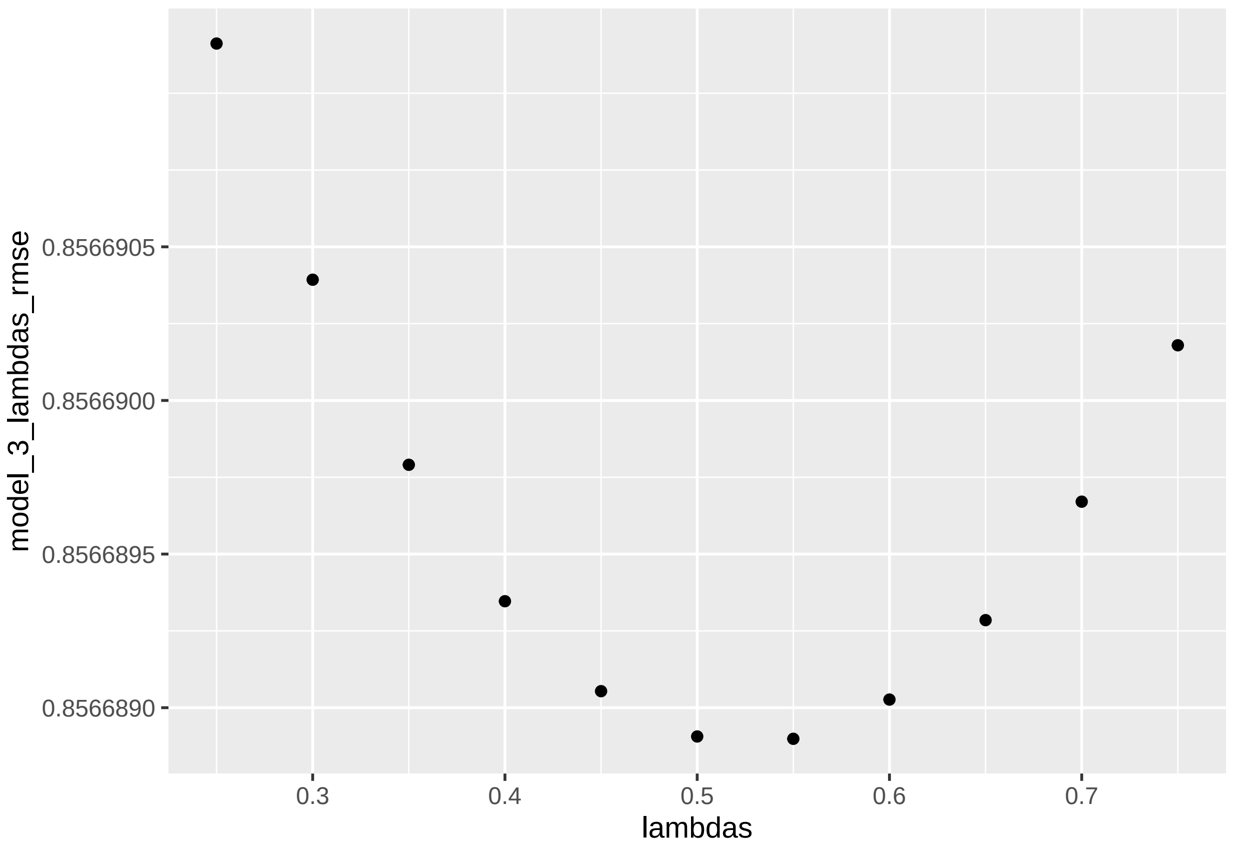


```
reg_reviewWeek_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    left_join(reg_user_avgs, by='userId') %>%
    left_join(reg_reviewYear_avgs, by='reviewYear') %>%
    group_by(reviewWeek) %>%
    summarize(b_w = sum(rating - mu - b_i - b_u - b_y)/(n()+1))

ggplot(aes(x=b_w), data=reg_reviewWeek_avgs) + geom_histogram(bins=10, alpha=0.8, color="black")
```



```
predict_model_3 <- function(df, l=0) {
  mu <- mean(edx$rating)

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

  reg_user_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(userId) %>%
    summarize(b_u = sum(rating - mu - b_i)/(n()+l))

  reg_reviewYear_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    left_join(reg_user_avgs, by='userId') %>%
    group_by(reviewYear) %>%
    summarize(b_y = sum(rating - mu - b_i - b_u)/(n()+l))

  reg_reviewWeek_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    left_join(reg_user_avgs, by='userId') %>%
    left_join(reg_reviewYear_avgs, by='reviewYear') %>%
    group_by(reviewWeek) %>%
    summarize(b_w = sum(rating - mu - b_i - b_u - b_y)/(n()+l))

  df %>%
```

```r
    left_join(reg_movie_avgs, by='movieId') %>%
    left_join(reg_user_avgs, by='userId') %>%
    left_join(reg_reviewYear_avgs, by='reviewYear') %>%
    # left_join(reg_reviewWeek_avgs, by='reviewWeek') %>%
    mutate(pred = mu + b_i + b_u + b_y) %>% .$pred
}

# Rudimental model execution timing for benchmarks
start_time <- Sys.time()
model_3_rmse <- RMSE(y, predict_model_3(edx, 0))
end_time <- Sys.time()
model_3_time <- end_time - start_time
preds_3 <- predict_model_3(edx, 0)

rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Model 3: Movie + User + reviewYearWeek Effect",
                                     RMSE = model_3_rmse,
                                     accuracy = mean(preds_3==y),
                                     lambda = 0,
                                     time = model_3_time
                                     ))

# Minimize the RMSE using a penalty factor
l_min <- 0
l_max <- 5
l_step <- .25
lambdas <- seq(l_min, l_max, l_step)

model_3_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_3(edx, l))
})
l <- lambdas[which.min(model_3_lambdas_rmse)]

l_min <- max(0, l-l_step)
l_max <- l+l_step
l_step <- l_step/5
lambdas <- seq(l_min, l_max, l_step)

model_3_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_3(edx, l))
})
l <- lambdas[which.min(model_3_lambdas_rmse)]
qplot(lambdas, model_3_lambdas_rmse)
```



```
if(l != 0) {
  preds_3l <- predict_model_3(edx, l)
  rmse_results <- bind_rows(rmse_results,
                            data_frame(
                              method="Model 3: Movie + User + reviewYearWeek Effect (reg)",
                              RMSE = min(model_3_lambdas_rmse),
                              accuracy = mean(preds_3l==y),
                              lambda = l,
                              time = model_3_time
                            ))
}
rm(lambdas, l, l_min, l_max, preds_3, preds_3l, start_time, end_time, model_3_time)
```

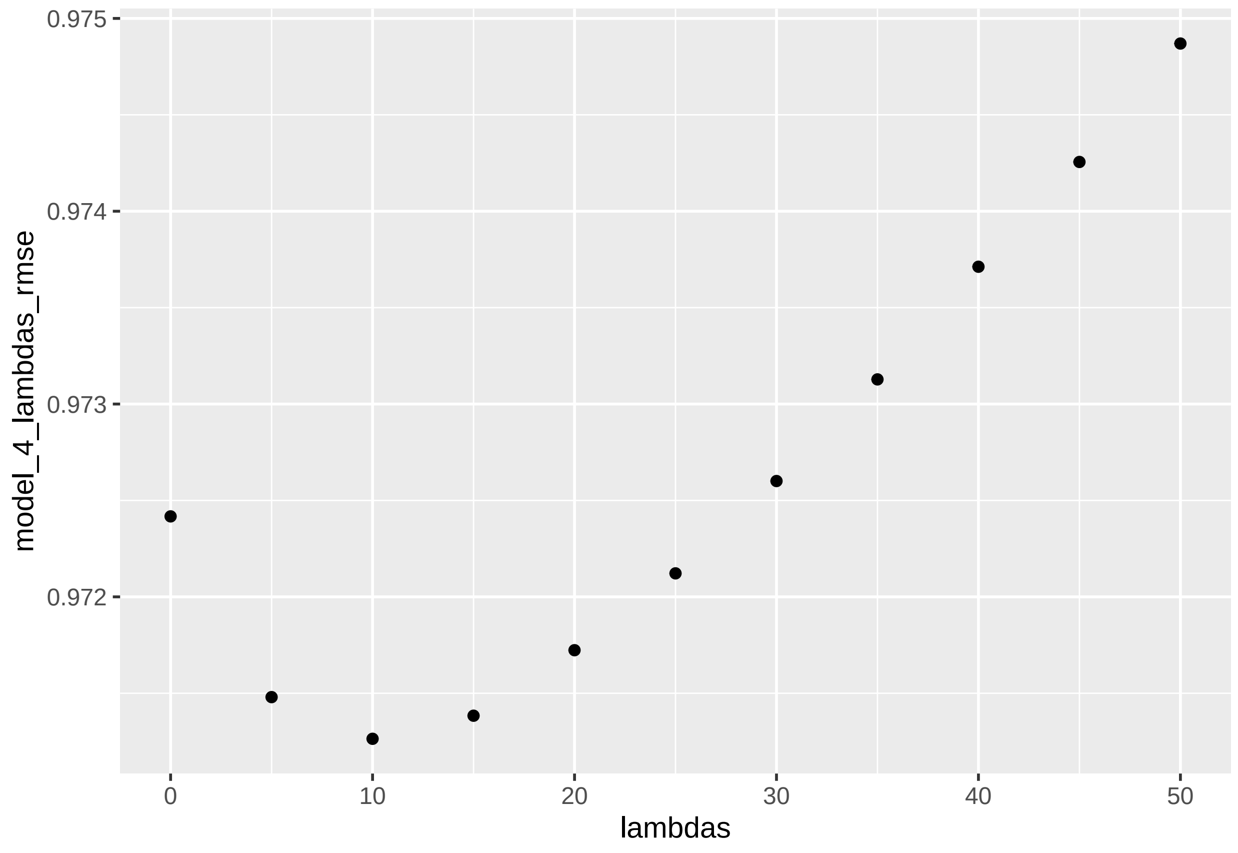
Despite the impact is moderate, taking in consideration also `reviewYear` and `reviewWeek` is slightly improving the RMSE.

7. Rounding -> don't

In order to provide exact predictions to match the true values, we should round our predictions in order to match an available rating option. We have seen in the data exploration sections that half-rating ratings have been introduced in 2003.

When predicting a rating, we can use this information to make sure that the prediction will be more accurate and see the impact. Since we will already include the `reviewYear` in our mode, we may discard the manipulation at point 6.

```r
## regularized reviewYear averages

uReviewYear <- sort(unique(edx$reviewYear))
ceiling_reviewYear <- tibble(
  reviewYear = uReviewYear,
  c_i = sapply(uReviewYear, function(x) { ifelse(as.numeric(levels(uReviewYear)[x]) >= 2003, 2, 1) })
)

l <- 0
predict_model_4 <- function(df, l=0) {
  mu <- mean(edx$rating)
  reg_movie_avgs <- edx %>%
   group_by(movieId) %>%
   summarize(b_i = sum(rating - mu)/(n()+l))

  reg_user_avgs <- edx %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(userId) %>%
    summarize(b_u = sum(rating - mu - b_i)/(n()+l))

  df %>%
   left_join(reg_movie_avgs, by='movieId') %>%
   left_join(reg_user_avgs, by='userId') %>%
   left_join(ceiling_reviewYear, by='reviewYear') %>%
   mutate(pred = ceiling((mu + b_i + b_u)*c_i)/c_i) %>% .$pred
}

# Rudimental model execution timing for benchmarks
start_time <- Sys.time()
preds_4 <- predict_model_4(edx, 0)
model_4_rmse <- RMSE(y, preds_4)
end_time <- Sys.time()
model_4_time <- end_time - start_time


rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Model 4: Movie + User Effect rounded",
                                     RMSE = model_4_rmse,
                                     accuracy = mean(preds_4==y),
                                     lambda = 0,
                                     time = model_4_time
                                     ))
# Minimize the RMSE by a penalty factor
l_min <- 0
l_max <- 50
l_step <- 5
lambdas <- seq(l_min, l_max, l_step)

model_4_lambdas_rmse <- sapply(lambdas, function(l) {
  RMSE(y, predict_model_4(edx, l))
})
l <- lambdas[which.min(model_4_lambdas_rmse)]
qplot(lambdas, model_4_lambdas_rmse)
```



```r
rm(preds_4, start_time, end_time, model_4_time)
```

As we will see in the results, the accuracy is still under 50% and the RMSE gets very bad. We may discard this option even if it was interesting to take in consideration

8. Cross-validation

In the first version of this report, the model was overfitting the edx set. In order to avoid this overfitting we can perform cross validation on several subset of the `edx` dataset

```r
generate_sets <- function (seed) {
  set.seed(seed, sample.kind="Rounding")
  test_index <- createDataPartition(y = edx$rating, times = 1, p = 0.1, list = FALSE)
  train_set <- edx[-test_index,]
  temp <- edx[test_index,]

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

  removed <- anti_join(temp, test_set, by=c("movieId", "userId"))
  train_set <- rbind(train_set, removed)

  rm(test_index, temp, removed)
  list(train_set, test_set)
}

predict_model <- function(train, test, l=0) {
  mu <- mean(train$rating)
  reg_movie_avgs <- train %>%
    group_by(movieId) %>%
    summarize(b_i = sum(rating - mu)/(n()+l))

  reg_user_avgs <- train %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    group_by(userId) %>%
    summarize(b_u = sum(rating - mu - b_i)/(n()+l))

  test %>%
    left_join(reg_movie_avgs, by='movieId') %>%
    left_join(reg_user_avgs, by='userId') %>%
    mutate(pred = mu + b_i + b_u) %>% .$pred
}

cross_validate <- function(seed) {
  lambdas <- seq(0,10,.25)
  sets <- generate_sets(seed)

  train_set <- sets[[1]]
  test_set <- sets[[2]]
  rm(sets)

  y <- test_set$rating

  sapply(lambdas, function(l){
    preds <- predict_model(train_set, test_set, l)
    RMSE(y, preds)
  })
}

lambdas <- seq(0,10,.25)
seeds <- seq(1, 50, 7)

rmses_matrix <- sapply(seeds, cross_validate)
colnames(rmses_matrix) <- seeds
rownames(rmses_matrix) <- lambdas
save(rmses_matrix, file = "./data/rmses_matrix.rda")
```

Let's visualize the result:

```r
load("data/rmses_matrix.rda")

colMeans(rmses_matrix)
```

```
##         1         8        15        22        29        36        43        50
## 0.8642755 0.8654374 0.8649130 0.8654868 0.8657095 0.8648669 0.8652598 0.8636925
```

```r
rowMeans(rmses_matrix)
```

```
##         0      0.25       0.5      0.75         1      1.25       1.5      1.75
## 0.8653841 0.8653069 0.8652407 0.8651825 0.8651306 0.8650843 0.8650428 0.8650058
##         2      2.25       2.5      2.75         3      3.25       3.5      3.75
## 0.8649727 0.8649435 0.8649177 0.8648952 0.8648758 0.8648592 0.8648454 0.8648341
##         4      4.25       4.5      4.75         5      5.25       5.5      5.75
## 0.8648252 0.8648187 0.8648144 0.8648121 0.8648119 0.8648135 0.8648169 0.8648220
##         6      6.25       6.5      6.75         7      7.25       7.5      7.75
## 0.8648288 0.8648372 0.8648470 0.8648583 0.8648709 0.8648849 0.8649001 0.8649165
##         8      8.25       8.5      8.75         9      9.25       9.5      9.75
## 0.8649341 0.8649527 0.8649725 0.8649932 0.8650150 0.8650376 0.8650612 0.8650857
##        10
## 0.8651109
```

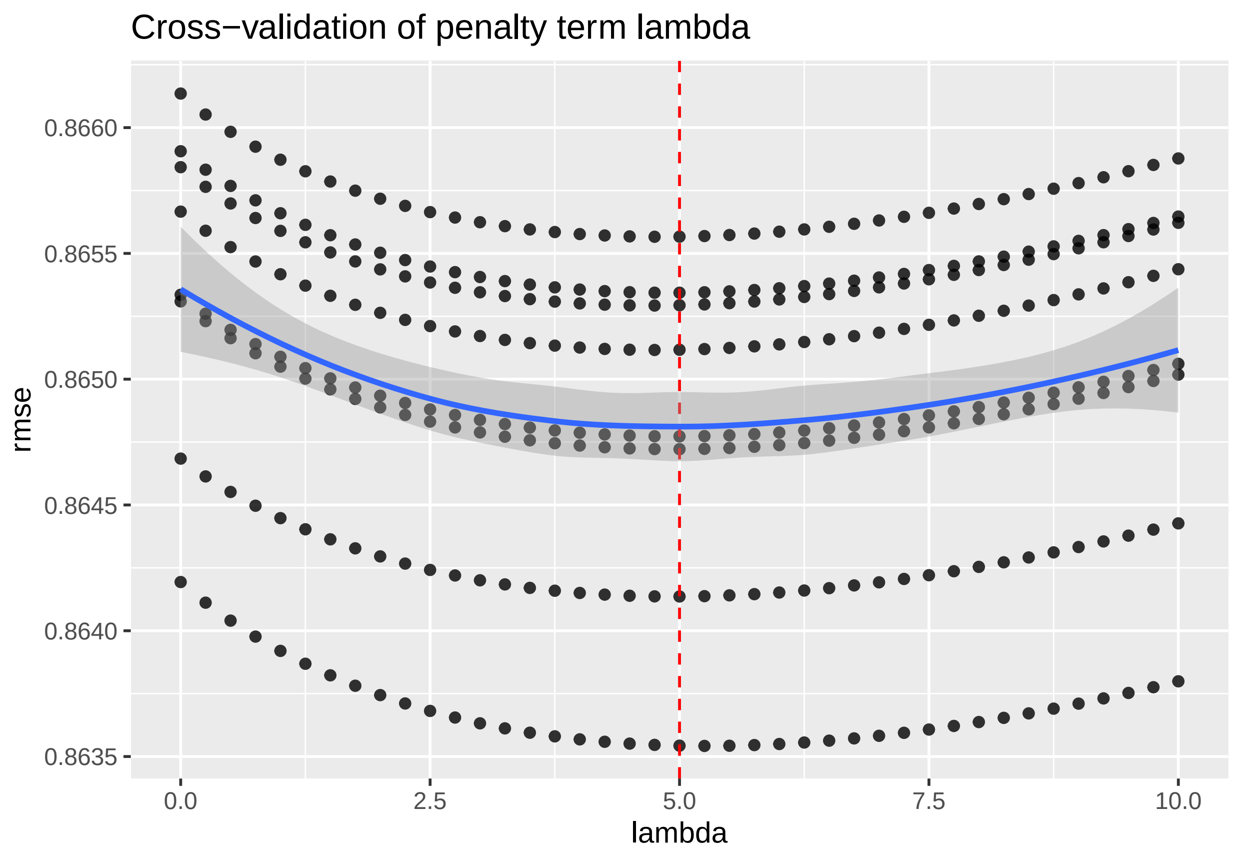
```r
lambdas <- seq(0,10,.25)

validation_lambda <- lambdas[which.min(rowMeans(rmses_matrix))]
validation_lambda
```

```
## [1] 5
```

```r
library(reshape2)
```

```
##
## Attaching package: 'reshape2'

## The following objects are masked from 'package:data.table':
##
##     dcast, melt

## The following object is masked from 'package:tidyr':
##
##     smiths
```

```r
melt(rmses_matrix, value.name = "rmse") %>%
  rename(lambda = Var1, seed = Var2) %>%
  ggplot(aes(x = lambda, y=rmse)) +
  geom_point(alpha = .8) +
  geom_vline(xintercept = validation_lambda,color="red", linetype="dashed") +
  geom_smooth(formula = y ~ x, method = "loess") +
  ggtitle("Cross-validation of penalty term lambda")
```



Results

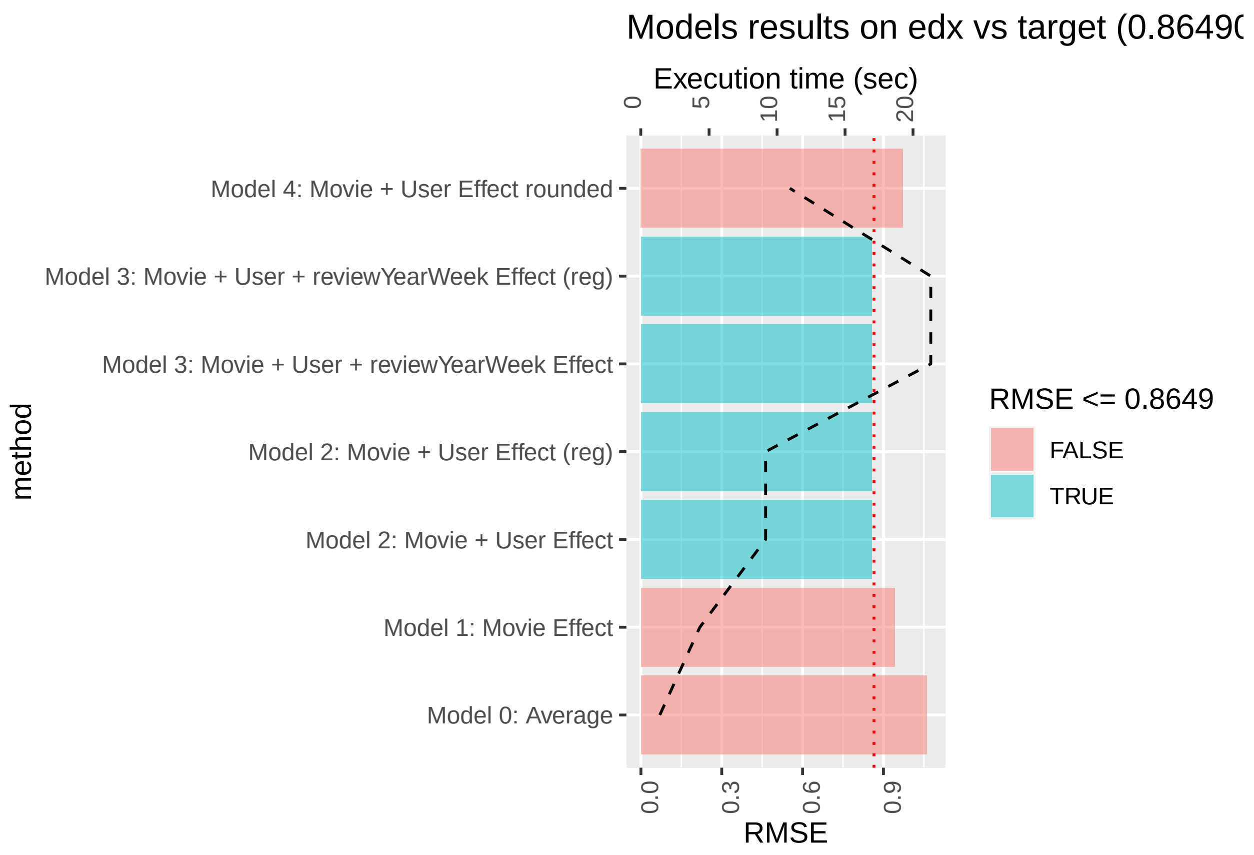
Let's see the results of the model developed on the `test_set`:

```r
rmse_results %>% kable(caption = "RMSE on edx dataset")
```

Table 7: RMSE on edx dataset

method	RMSE	accuracy	lambda	time
Model 0: Average	1.0603313	0.0000000	0.00	1.388187 secs
Model 1: Movie Effect	0.9423475	0.0002501	0.00	4.331467 secs
Model 2: Movie + User Effect	0.8567039	0.0000000	0.00	9.166731 secs
Model 2: Movie + User Effect (reg)	0.8566952	0.0000000	0.50	9.166731 secs
Model 3: Movie + User + reviewYearWeek Effect	0.8566979	0.0000000	0.00	21.302904 secs
Model 3: Movie + User + reviewYearWeek Effect (reg)	0.8566889	0.0000000	0.55	21.302904 secs
Model 4: Movie + User Effect rounded	0.9724173	0.3433422	0.00	10.945627 secs

```r
ggplot(rmse_results, aes(x=method, fill=RMSE <= 0.86490, group=1)) +
  geom_bar(aes(y=RMSE), stat ="identity", alpha = 0.5) +
  geom_hline(yintercept = 0.86490, linetype = "dotted", color = "red") +
  geom_line(aes(y = (max(rmse_results$RMSE)/as.integer(max(rmse_results$time)))*time), linetype = "dashe
  scale_y_continuous(sec.axis = sec_axis(~./(max(rmse_results$RMSE)/as.integer(max(rmse_results$time)))
  ggtitle("Models results on edx vs target (0.86490)") +  theme(axis.text.x = element_text(angle = 90,
  coord_flip()
```



We can clearly see that on the training dataset `edx` our prediction 0.8566889 was considerably lower the target *RMSE < 0.86490*.

Looking at the results, `model_3` training was very long to run compares to other models. The benefit in terms of RMSE may not justify the consumption of resources and time (10ˆ-5 impact).

When trying to introduce the round to increase the accuracy the RMSE became insufficient and the accuracy did not exceed 34%.

Given the results obtained, we would stick on model 2 taking in consideration only movie and user effect.

Since the model tuning was overfitted for `edx` dataset, I performed some cross-validation by sampling 8 different `train_set` and `test_set`. This allowed to identify the `validation_lambda`.

The result on the `validation` dataset is

```
final_RMSE <- RMSE(validation$rating, predict_model_2(validation, validation_lambda))
# 0.8652226
final_RMSE
```

```
## [1] 0.8648177
```

The final RMSE is 0.8648177.

Conclusion

Working with Big Data can be really challenging.