PH125.9x - Capstone: MovieLens Project

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Abstract

This project creates a movie recommendation system using the 10M version of the MovieLens dataset. In addition to movie and user effects, 'title' and 'timestamp' variables are used to extract movies' release years, and calculate a new rate timestamp indicator, incorporating all four effects in the final model, which are also regularized by a tuning parameter of 0.5 chosen through cross-validation. The final model reaches a residual mean squared error (RMSE) ~ 0.8647 when employed on the Validation Set, which is lower than the project's target.

Keywords: movielens, recommendation system, EDA, capstone, r markdown

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1 Introduction

MovieLens (https://movielens.org/) is a website run by GroupLens, a research lab at the University of Minnesota. It works as a collaborative movie recommendation system, based on their film preferences or taste profile, measured employing Machine Learning tools on users' movie ratings and movie reviews (Harper & Konstan, 2015).

In this project, we will be working with the MovieLens 10M 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. Unlike previous MovieLens data sets, no demographic information is included. 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. Also included are scripts for generating subsets of the data to support five-fold cross-validation of rating predictions. More details about the contents and use of all these files follows.

The project approach is to build a model using a train set that minimizes the loss function by considering the following effects:

- *Movie*: The rating can be predicted based on other users' evaluation of the movie.
- *User*: It can also be predicted by the user's usual rating to watched movies.
- *Release Year*: Improves the algorithm by grouping movies with its yearly competitors.
- *Rate Timestamp*: Number of years between release and moment when the rate was given, improving the model by considering the movie's gained popularity.

After that, the model is regularized with a tuning parameter chosen through cross-validation, in order to penalize large estimates that are formed using small sample sizes (Irizarry, 2020). A residual mean squared error (`RMSE`) was used as the loss function (the typical error we make when predicting a movie rating) for performance measure.

2 Methodology

As the first step, we downloaded the MovieLens dataset with the code provided in the course. Once we had a train set, we analyzed some of its properties through descriptive statistics and histograms, in order to gain insights for the prediction model. Then, we added the movie's release year and rate timestamp to the dataset, in order to use them as predictors.

Finally, the model was built using movie, user, release year and rate timestamp effects on the `edx` set. The effects were later regularized looking for a tuning parameter (λ) that minimized the `RMSE`. Every intermediate result obtained was compared to the `RMSE < 0.8649` goal.

2.1 Data extraction

Code provided on the `Course/Capstone Project: All Learners/Project Overview: MovieLens` section of the `PH125.9x - Capstone: MovieLens Project` course.

```r
# Import libraries
rm(list=ls())

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")
if(!require(ggplot2))
  install.packages("ggplot2", repos = "http://cran.us.r-project.org")
if(!require(knitr))
  install.packages("knitr", repos = "http://cran.us.r-project.org")

library(tidyverse)
library(caret)
```

```r
library(data.table)
library(ggplot2)
library(knitr)

# Get from URL or download file in Documents
zip_file <- "~/ml-10m.zip"
if(file.exists(zip_file)) {dl <- zip_file} else {
  dl <- tempfile()
  download.file("http://files.grouplens.org/datasets/movielens/ml-10m.zip",
                dl)
}

# Unzip and read data
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(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 = F)
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)
```

2.2 Data description

The edx train set contains 9,000,055 rows and 6 columns, each variable meaning: userId of the rater, movieId, title and genres of the movie rated, timestamp of the information, and the rating gave by the user, which goes from 0.5 to 5.0 stars.

```r
dim(edx)
```

```
## [1] 9000055       6
```

```r
head(edx) %>% as.tibble()
```

```
## # A tibble: 6 x 6
##   userId movieId rating timestamp title                   genres
##    <int>   <dbl>  <dbl>     <int> <chr>                   <chr>
## 1      1     122      5 838985046 Boomerang (1992)        Comedy|Romance
## 2      1     185      5 838983525 Net, The (1995)         Action|Crime|Thriller
## 3      1     292      5 838983421 Outbreak (1995)         Action|Drama|Sci-Fi|T~
## 4      1     316      5 838983392 Stargate (1994)         Action|Adventure|Sci-~
## 5      1     329      5 838983392 Star Trek: Generations~ Action|Adventure|Dram~
## 6      1     355      5 838984474 Flintstones, The (1994) Children|Comedy|Fanta~
```

We can analyze the train set using some descriptive statistics.

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

Notice that there are 69,878 and 10,677 different users and movies, respectively.

```r
summarize(edx,
          unique_users = n_distinct(userId),
          unique_movies = n_distinct(movieId))
```

```
##   unique_users unique_movies
## 1        69878         10677
```

Here we can see the top 50 best ranking movies, and how many votes each one received.

```r
edx %>% group_by(movieId) %>%
  summarise(stars = mean(rating),
            votes = n()) %>%
  left_join(edx, by = "movieId") %>%
  select(movieId, title, votes, stars) %>%
  unique() %>%
  filter(title != "NA") %>%
  arrange(desc(stars)) %>%
  slice(1:50) %>%
  mutate(ranking = 1:n()) %>%
  select(ranking, everything()) %>%
  kable()
```

ranking	movieId	title	votes	stars
1	3226	Hellhounds on My Trail (1999)	1	5.000000
2	33264	Satan's Tango (SÃ¡tÃ¡ntangÃ³) (1994)	2	5.000000
3	42783	Shadows of Forgotten Ancestors (1964)	1	5.000000
4	51209	Fighting Elegy (Kenka erejii) (1966)	1	5.000000
5	53355	Sun Alley (Sonnenallee) (1999)	1	5.000000
6	64275	Blue Light, The (Das Blaue Licht) (1932)	1	5.000000
7	5194	Who's Singin' Over There? (a.k.a. Who Sings Over There) (Ko to tamo peva) (1980)	4	4.750000
8	26048	Human Condition II, The (Ningen no joken II) (1959)	4	4.750000
9	26073	Human Condition III, The (Ningen no joken III) (1961)	4	4.750000
10	65001	Constantine's Sword (2007)	2	4.750000
11	4454	More (1998)	7	4.714286
12	5849	I'm Starting From Three (Ricomincio da Tre) (1981)	3	4.666667
13	63808	Class, The (Entre les Murs) (2008)	3	4.666667
14	7452	Mickey (2003)	1	4.500000
15	7823	Demon Lover Diary (1980)	1	4.500000
16	25975	Life of Oharu, The (Saikaku ichidai onna) (1952)	3	4.500000
17	38320	Valerie and Her Week of Wonders (Valerie a tÃ½den divu) (1970)	1	4.500000
18	50477	Testament of Orpheus, The (Testament d'OrphÃ©e) (1960)	1	4.500000
19	53883	Power of Nightmares: The Rise of the Politics of Fear, The (2004)	4	4.500000

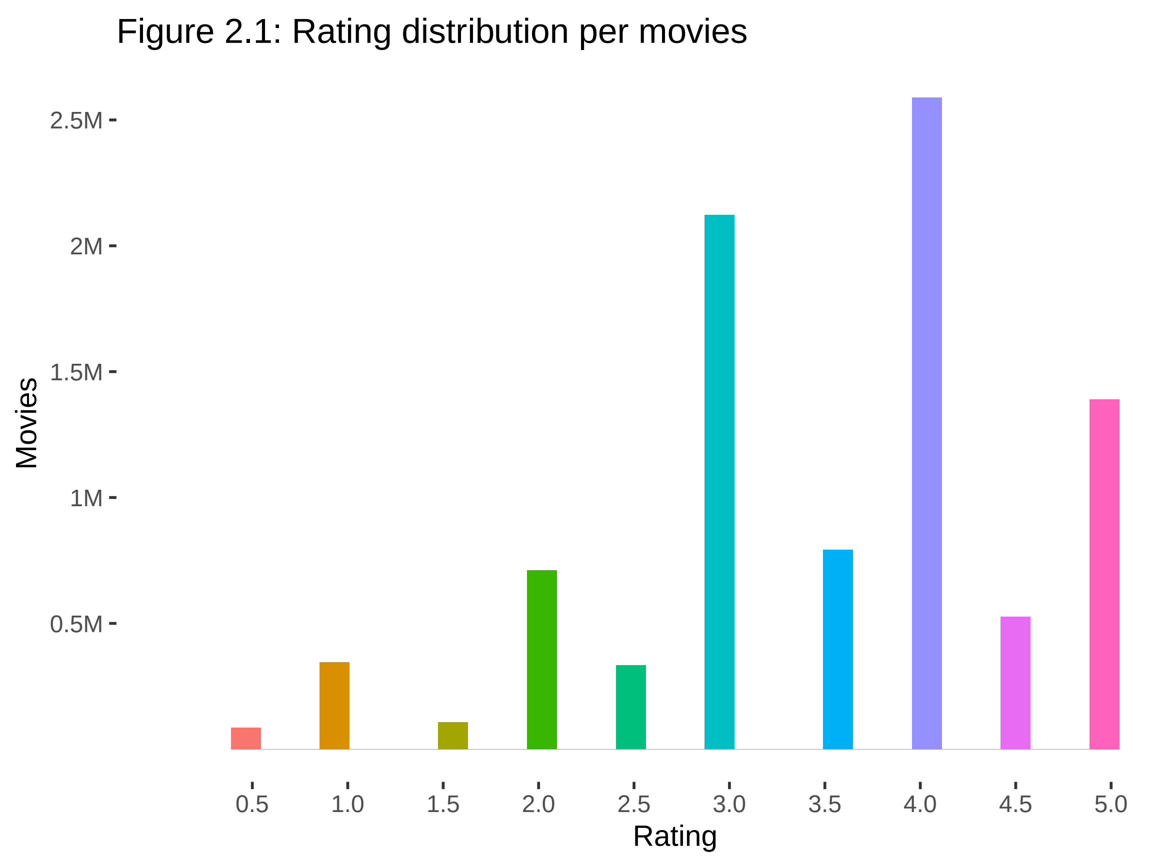
ranking	movieId	title	votes	stars
20	56015	Kansas City Confidential (1952)	1	4.500000
21	58185	Please Vote for Me (2007)	1	4.500000
22	60336	Bad Blood (Mauvais sang) (1986)	1	4.500000
23	60990	End of Summer, The (Kohayagawa-ke no aki) (1961)	3	4.500000
24	61695	Ladrones (2007)	1	4.500000
25	63179	Tokyo! (2008)	1	4.500000
26	64418	Man Named Pearl, A (2006)	1	4.500000
27	318	Shawshank Redemption, The (1994)	28015	4.455131
28	32792	Red Desert, The (Deserto rosso, Il) (1964)	6	4.416667
29	858	Godfather, The (1972)	17747	4.415366
30	32657	Man Who Planted Trees, The (Homme qui plantait des arbres, L') (1987)	5	4.400000
31	50	Usual Suspects, The (1995)	21648	4.365854
32	527	Schindler's List (1993)	23193	4.363493
33	31309	Rocco and His Brothers (Rocco e i suoi fratelli) (1960)	3	4.333333
34	58808	Last Hangman, The (2005)	3	4.333333
35	912	Casablanca (1942)	11232	4.320424
36	904	Rear Window (1954)	7935	4.318651
37	922	Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	2922	4.315880
38	1212	Third Man, The (1949)	2967	4.311426
39	3435	Double Indemnity (1944)	2154	4.310817
40	1178	Paths of Glory (1957)	1571	4.308721
41	2019	Seven Samurai (Shichinin no samurai) (1954)	5190	4.306744
42	1221	Godfather: Part II, The (1974)	11920	4.301971
43	58559	Dark Knight, The (2008)	2353	4.297068
44	750	Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1964)	10627	4.295333
45	1193	One Flew Over the Cuckoo's Nest (1975)	13014	4.293261
46	44555	Lives of Others, The (Das Leben der Anderen) (2006)	1108	4.291065
47	3030	Yojimbo (1961)	1528	4.281741
48	1148	Wallace & Gromit: The Wrong Trousers (1993)	7167	4.275429
49	745	Wallace & Gromit: A Close Shave (1995)	5690	4.275308
50	1260	M (1931)	1926	4.274662

2.3 Data visualization

The most popular ratings are `4.0` and `3.0`, while half stars ratings are less common.

```r
# Rating histogram
y_cuts <- c(0.5, 1.0, 1.5, 2.0, 2.5)
edx %>%
  ggplot(aes(rating, fill = cut(rating, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "Rating", y = "Movies") +
```

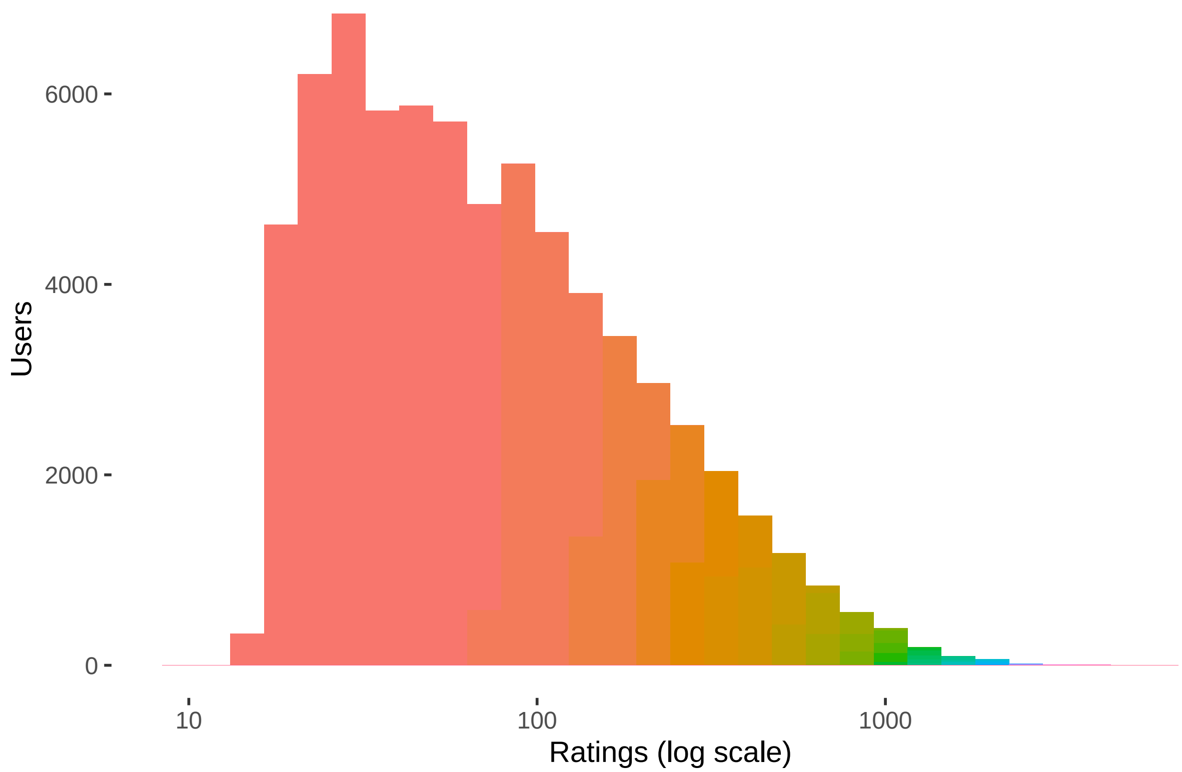
```
  ggtitle("Figure 2.1: Rating distribution per movies") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white")) +
  scale_x_discrete(limits = c(seq(min(edx$rating),
                                  max(edx$rating),
                                  max(edx$rating)/n_distinct(edx$rating))))+
  scale_y_continuous(labels = paste0(y_cuts, "M"),
                     breaks = y_cuts * 10^6)
```



Users usually rate less than `100` different movies, and very few more than `1000`.

```
# Ratings per users histogram
edx %>% count(userId) %>%
  ggplot(aes(n, fill = cut(n, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "Ratings (log scale)", y = "Users") +
  ggtitle("Figure 2.2: Ratings per users") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white")) +
  scale_x_log10()
```

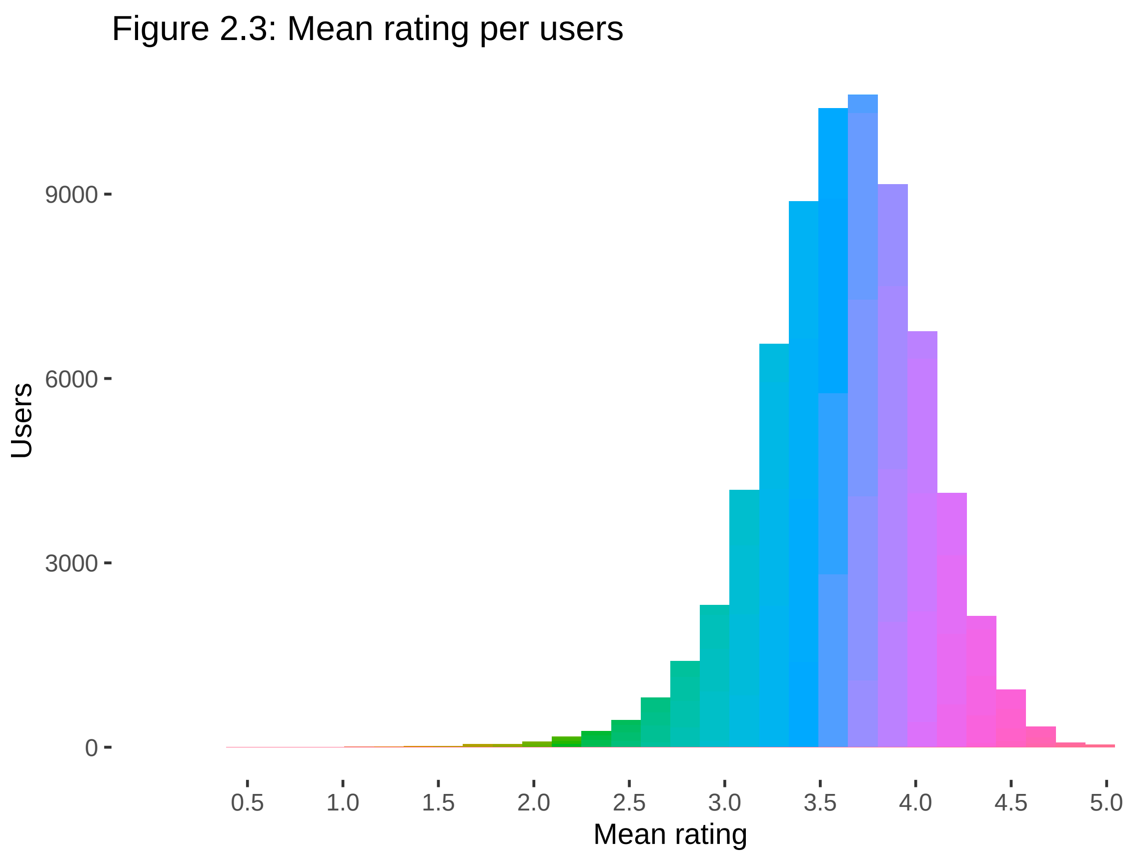
Figure 2.2: Ratings per users



Mean rating is between `3.5` and `4.0`.

```
# Mean rating per users histogram
edx %>% group_by(userId) %>%
  summarise(m = mean(rating)) %>%
  ggplot(aes(m, fill = cut(m, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "Mean rating", y = "Users") +
  ggtitle("Figure 2.3: Mean rating per users") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white")) +
  scale_x_discrete(limits = c(seq(min(edx$rating),
                                  max(edx$rating),
                                  max(edx$rating)/n_distinct(edx$rating))))
```

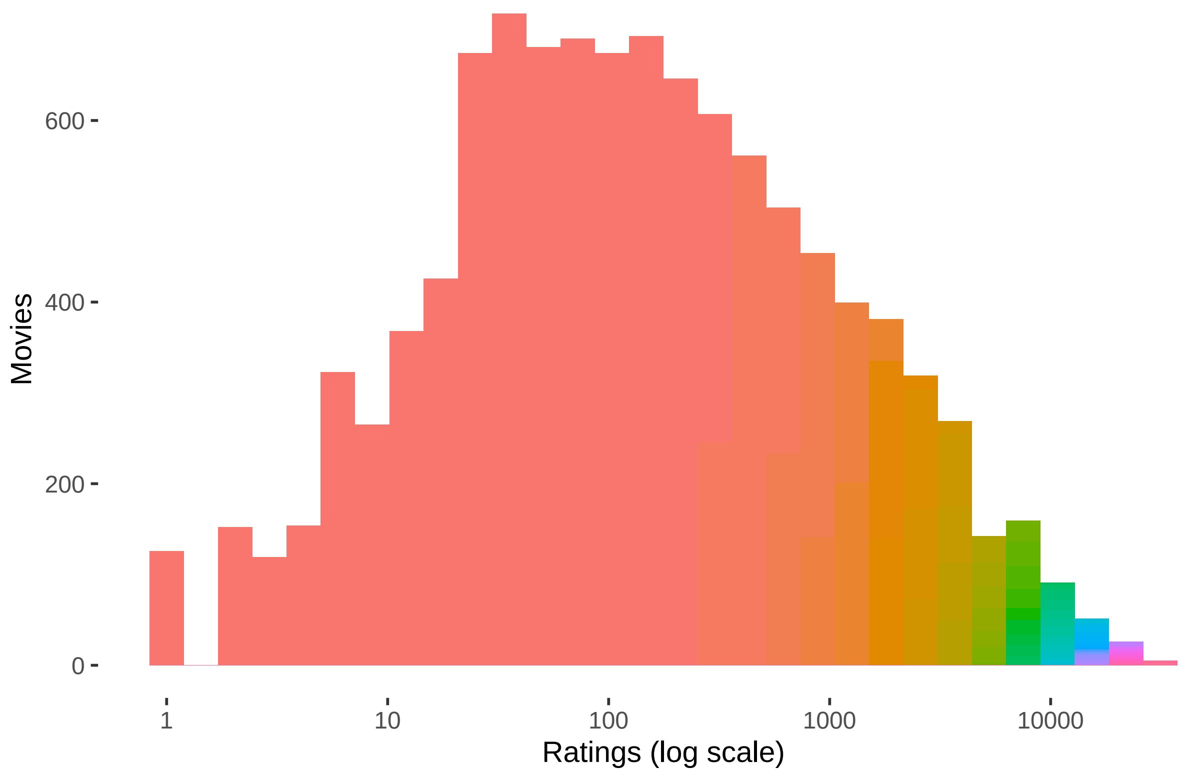
```
## Warning: Continuous limits supplied to discrete scale.
## Did you mean `limits = factor(...)` or `scale_*_continuous()`?
```



On the other hand, less than ten movies have received less than ten ratings. But also less than `400` have received more than `1000` ratings.

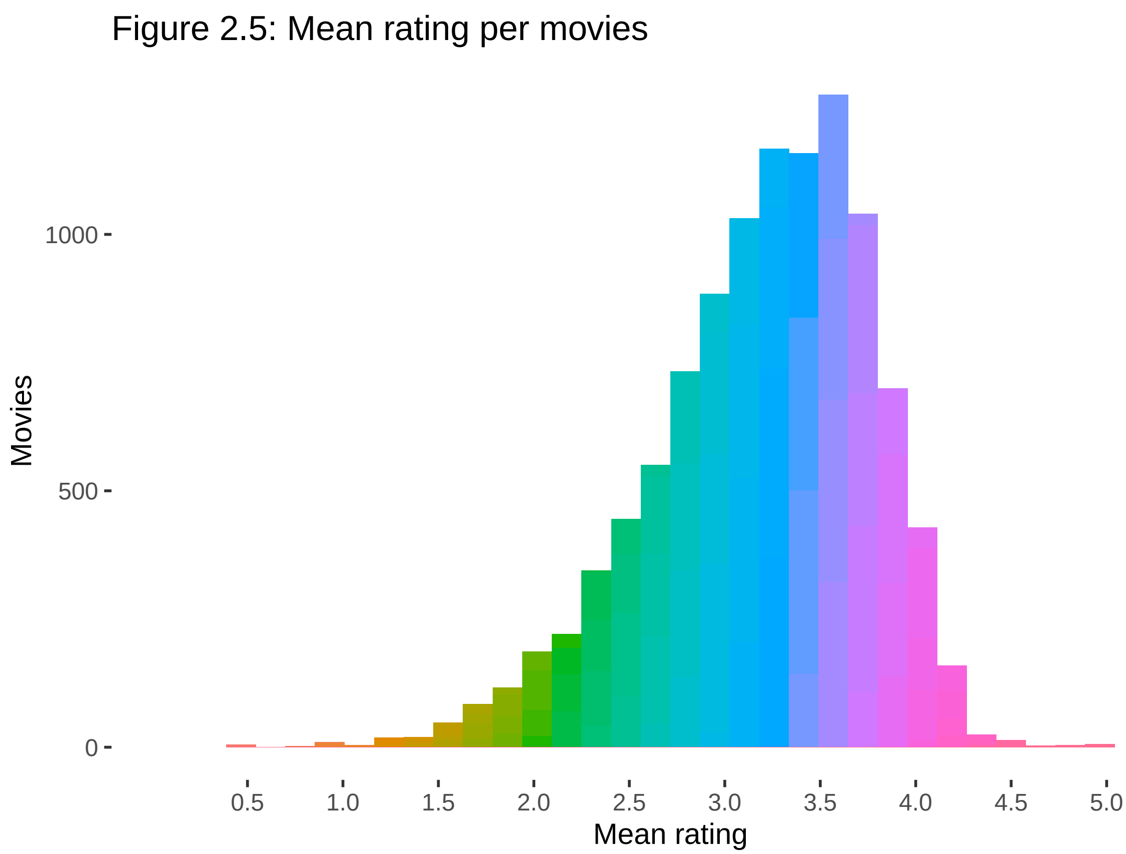
```
# Ratings per movies histogram
edx %>% count(movieId) %>%
  ggplot(aes(n, fill = cut(n, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "Ratings (log scale)", y = "Movies") +
  ggtitle("Figure 2.4: Ratings per movies") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white")) +
  scale_x_log10()
```

Figure 2.4: Ratings per movies



Mean rating is near `3.5`.

```
# Mean rating per movies histogram
edx %>% group_by(movieId) %>%
  summarise(m = mean(rating)) %>%
  ggplot(aes(m, fill = cut(m, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "Mean rating", y = "Movies") +
  ggtitle("Figure 2.5: Mean rating per movies") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white")) +
  scale_x_discrete(limits = c(seq(min(edx$rating),
                                  max(edx$rating),
                                  max(edx$rating)/n_distinct(edx$rating))))
```



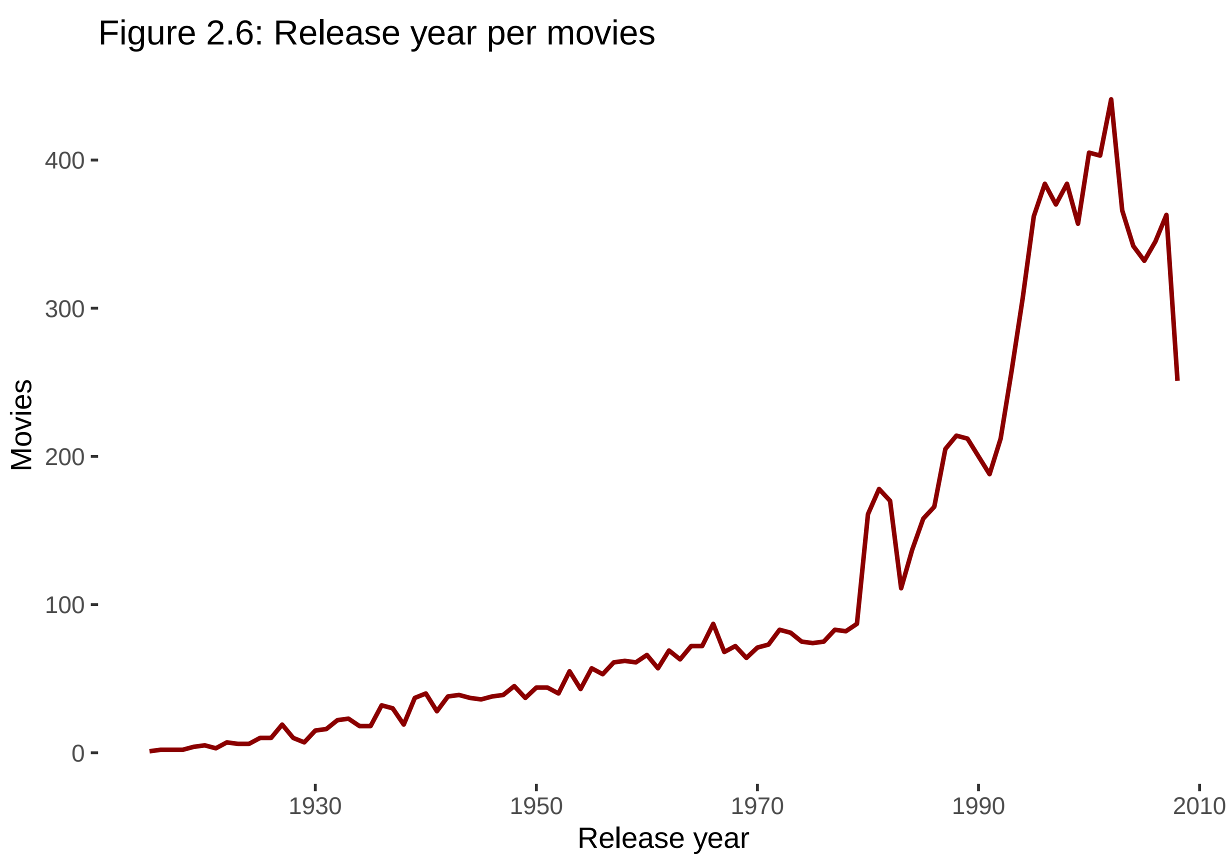
2.4 Data calculations

Notice that the data's timestamp can be transformed using January 1st, 1970 as initial date. We can also extract the release year from the title, and using both years we can calculate the rate timestamp.

```
# Dates addition
edx <- edx %>%
  mutate(timestamp = as.POSIXct(timestamp,
                                origin = "1970-01-01",
                                tz = "GMT"),
         year_movie = as.numeric(substr(title,
                                        nchar(title)-4,
                                        nchar(title)-1)),
         year_rated = as.numeric(format(timestamp, "%Y")),
         rate_ts = year_rated - year_movie)
```

There are less than 100 movies per year for movies released before 1980, but more than 200 for those released after 1990.

```r
edx %>%
  select(movieId, year_movie) %>%
  unique() %>%
  group_by(year_movie) %>%
  summarise(count = n()) %>%
  ggplot(aes(year_movie, count)) +
  geom_line(color = "darkred",
            size = 0.8) +
  labs(x = "Release year", y = "Movies") +
  ggtitle("Figure 2.6: Release year per movies") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white"))
```



2.5 Data modeling

Now we make a naive prediction based on the average rating, and from there, we can build the model adding movie, user, release year and rate timestamp effects. Finally, we regularize these effects to minimize the `RMSE`.

```r
# Summary statistics
mu <- mean(edx$rating)
```

The average rating ($\mu = 3.5124652$) is used to make a naive prediction. We obtain `RMSE = 1.06`, meaning our predictions are on average more than one star far from the actual value.

```r
# Average prediction
rmse_naive <- RMSE(edx$rating, mu)
rmse_results <- tibble(Model = "01. Average only",
                       RMSE = rmse_naive,
                       Goal = ifelse(rmse_naive < 0.8649, "Under", "Over"))
```

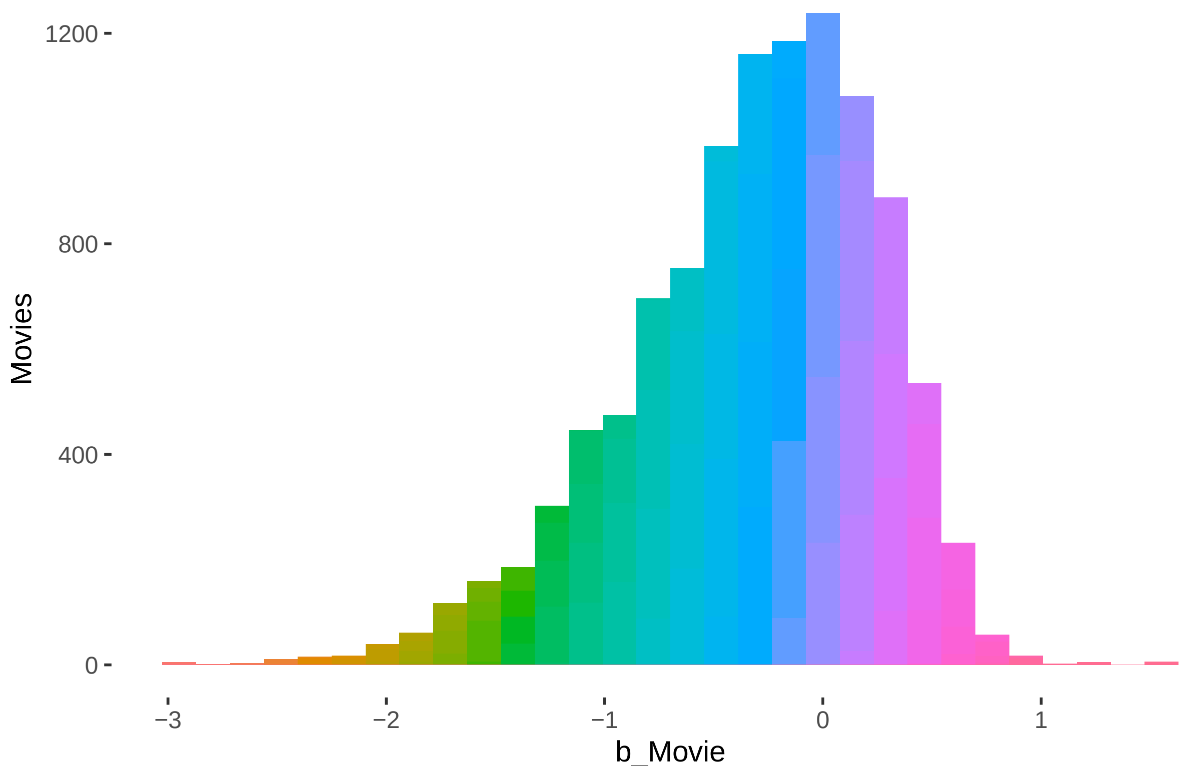
Model	RMSE	Goal
01. Average only	1.060331	Over

Now we will start incorporating the movie effect, which generates a `RMSE = 0.9423`.

```r
# Movie effect prediction
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarise(b_Movie = mean(rating - mu))

movie_avgs %>%
  ggplot(aes(b_Movie, fill = cut(b_Movie, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "b_Movie", y = "Movies") +
  ggtitle("Figure 3.1: Movies per computed b_Movie") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white"))
```

Figure 3.1: Movies per computed b_Movie




```
predicts_movie <- mu + edx %>%
  left_join(movie_avgs, by = "movieId") %>%
  pull(b_Movie)

rmse_model1 <- RMSE(predicts_movie, edx$rating)

rmse_results <- rmse_results %>%
  bind_rows(tibble(Model = "02. Movie Effect",
                   RMSE = rmse_model1,
                   Goal = ifelse(rmse_model1 < 0.8649, "Under", "Over")))
```

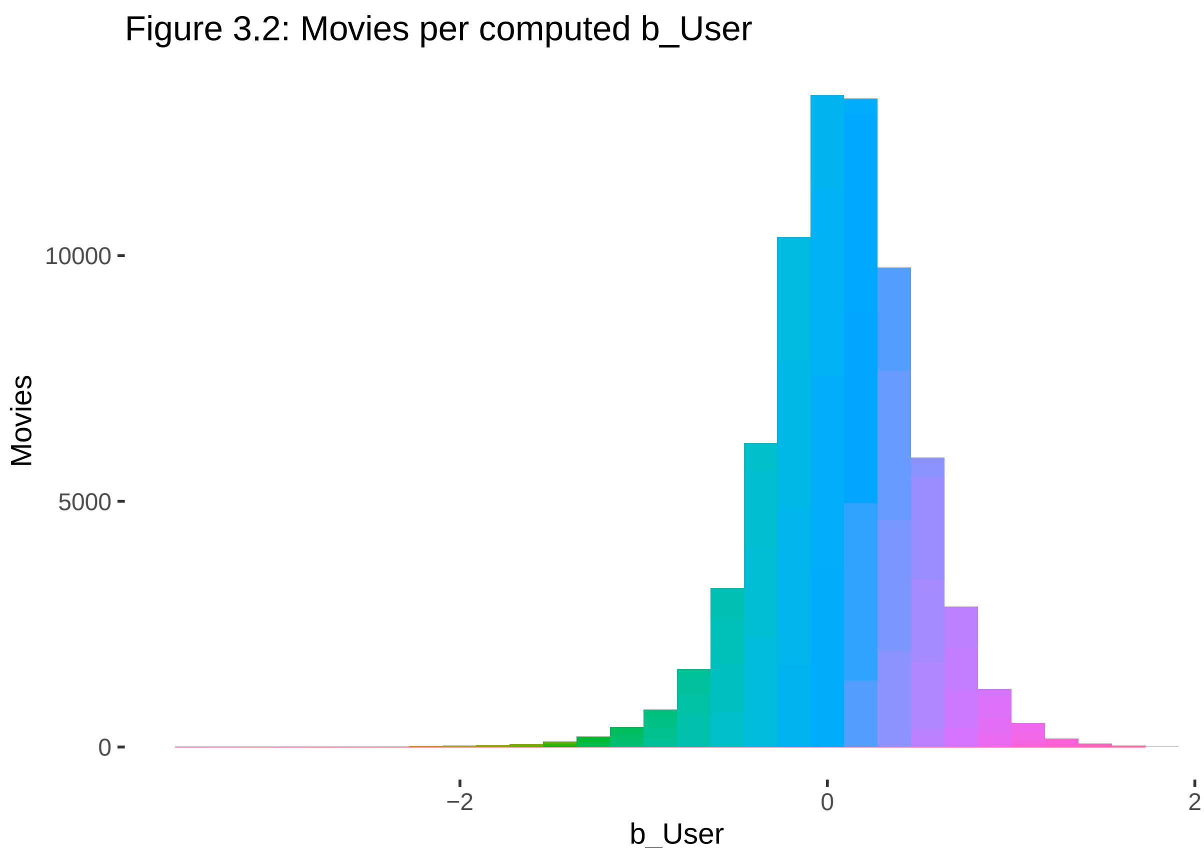
Model	RMSE	Goal
01. Average only	1.0603313	Over
02. Movie Effect	0.9423475	Over

Then we add the user effect. With this two, we get a `RMSE = 0.8567`, which is lower than the target.

```
# Movie and user effect prediction
user_avgs <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
```

```
  group_by(userId) %>%
  summarise(b_User = mean(rating - b_Movie - mu))

user_avgs %>%
  ggplot(aes(b_User, fill = cut(b_User, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "b_User", y = "Movies") +
  ggtitle("Figure 3.2: Movies per computed b_User") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white"))
```




```
predicts_movie_user <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
  left_join(user_avgs, by = "userId") %>%
  mutate(pred = mu + b_Movie + b_User) %>%
  pull(pred)

rmse_model2 <- RMSE(predicts_movie_user,
                    edx$rating)
rmse_results <- rmse_results %>%
```

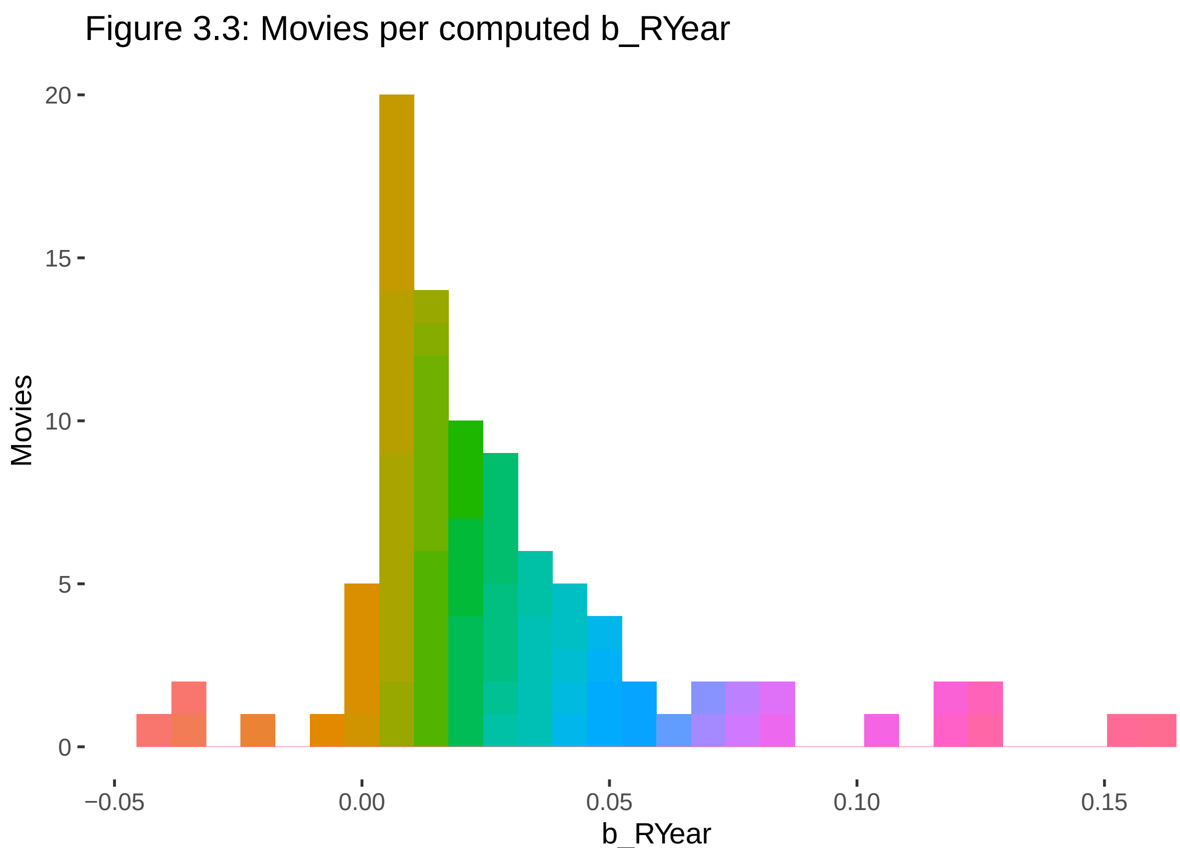
```r
  bind_rows(tibble(Model = "03. +User Effect",
                   RMSE = rmse_model2,
                   Goal = ifelse(rmse_model2 < 0.8649, "Under", "Over")))
```

Model	RMSE	Goal
01. Average only	1.0603313	Over
02. Movie Effect	0.9423475	Over
03. +User Effect	0.8567039	Under

Then, we incorporate the release year effect, getting a `RMSE = 0.8564`. We can see how β *RYear* values are approaching `0`.

```r
# Movie, user and release year effect prediction
RYear_avgs <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
  left_join(user_avgs, by = "userId") %>%
  group_by(year_movie) %>%
  summarise(b_RYear = mean(rating - b_User - b_Movie - mu))

RYear_avgs %>%
  ggplot(aes(b_RYear, fill = cut(b_RYear, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "b_RYear", y = "Movies") +
  ggtitle("Figure 3.3: Movies per computed b_RYear") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white"))
```




```
predicts_movie_user_RYear <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
  left_join(user_avgs, by = "userId") %>%
  left_join(RYear_avgs, by = "year_movie") %>%
  mutate(pred = mu + b_Movie + b_User + b_RYear) %>%
  pull(pred)

rmse_model3 <- RMSE(predicts_movie_user_RYear,
                    edx$rating)
rmse_results <- rmse_results %>%
  bind_rows(tibble(Model = "04. +RYear Effect",
                   RMSE = rmse_model3,
                   Goal = ifelse(rmse_model3 < 0.8649, "Under", "Over")))
```

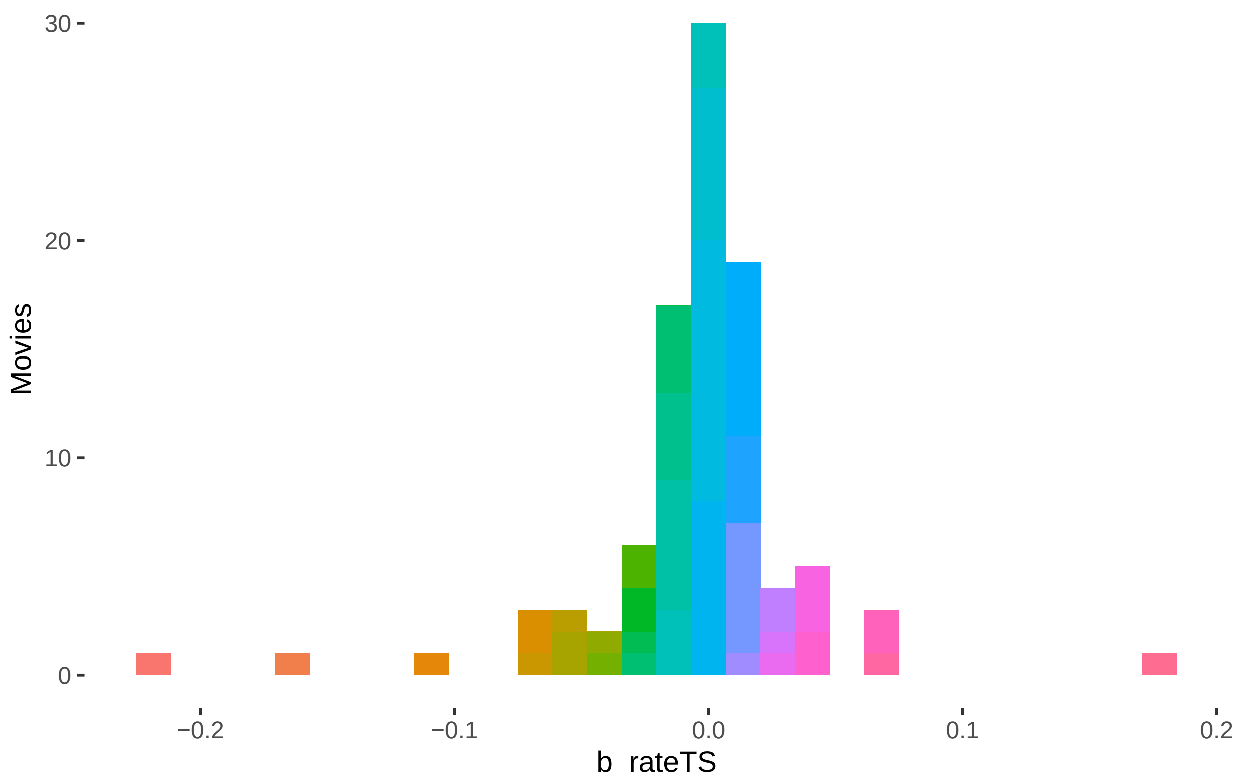
Model	RMSE	Goal
01. Average only	1.0603313	Over
02. Movie Effect	0.9423475	Over
03. +User Effect	0.8567039	Under
04. +RYear Effect	0.8563777	Under

Our fourth and final effect is rate timestamp, giving a `RMSE = 0.8561`. Most values of β *rateTS* are closer to 0 from less than 0.1.

```
# Movie, user, release year and rate timestamp effect prediction
rateTS_avgs <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
  left_join(user_avgs, by = "userId") %>%
  left_join(RYear_avgs, by = "year_movie") %>%
  group_by(rate_ts) %>%
  summarise(b_rateTS = mean(rating - b_RYear - b_User - b_Movie - mu))

rateTS_avgs %>%
  ggplot(aes(b_rateTS, fill = cut(b_rateTS, 100))) +
  geom_histogram(bins = 30, show.legend = F) +
  theme_update() +
  labs(x = "b_rateTS", y = "Movies") +
  ggtitle("Figure 3.4: Movies per computed b_rateTS") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white"))
```

Figure 3.4: Movies per computed b_rateTS




```
predicts_movie_user_RYear_rateTS <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
```

```r
  left_join(user_avgs, by = "userId") %>%
  left_join(RYear_avgs, by = "year_movie") %>%
  left_join(rateTS_avgs, by = "rate_ts") %>%
  mutate(pred = mu + b_rateTS + b_RYear + b_User + b_Movie) %>%
  pull(pred)

rmse_model4 <- RMSE(predicts_movie_user_RYear_rateTS,
                    edx$rating)
rmse_results <- rmse_results %>%
  bind_rows(tibble(Model = "05. +RateTS Effect",
                   RMSE = rmse_model4,
                   Goal = ifelse(rmse_model4 < 0.8649, "Under", "Over")))
```

Model	RMSE	Goal
01. Average only	1.0603313	Over
02. Movie Effect	0.9423475	Over
03. +User Effect	0.8567039	Under
04. +RYear Effect	0.8563777	Under
05. +RateTS Effect	0.8560683	Under

Now we can regularize our model. We use cross validation with a vector of tuning parameters from `0` to `5`, increasing on `0.25`. The result is an optimal λ= `0.5`.

```r
# Regularized effects
lambdas <- seq(0, 5, 0.25)

RMSEs <- sapply(lambdas, function(l){

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

  b_User <- edx %>%
    left_join(b_Movie, by = "movieId") %>%
    group_by(userId) %>%
    summarise(b_User = sum(rating - mu - b_Movie)/(n() + l))

  b_RYear <- edx %>%
    left_join(b_Movie, by = "movieId") %>%
    left_join(b_User, by = "userId") %>%
    group_by(year_movie) %>%
    summarise(b_RYear = sum(rating - mu - b_Movie - b_User)/(n() + l))

  b_rateTS <- edx %>%
    left_join(b_Movie, by = "movieId") %>%
```

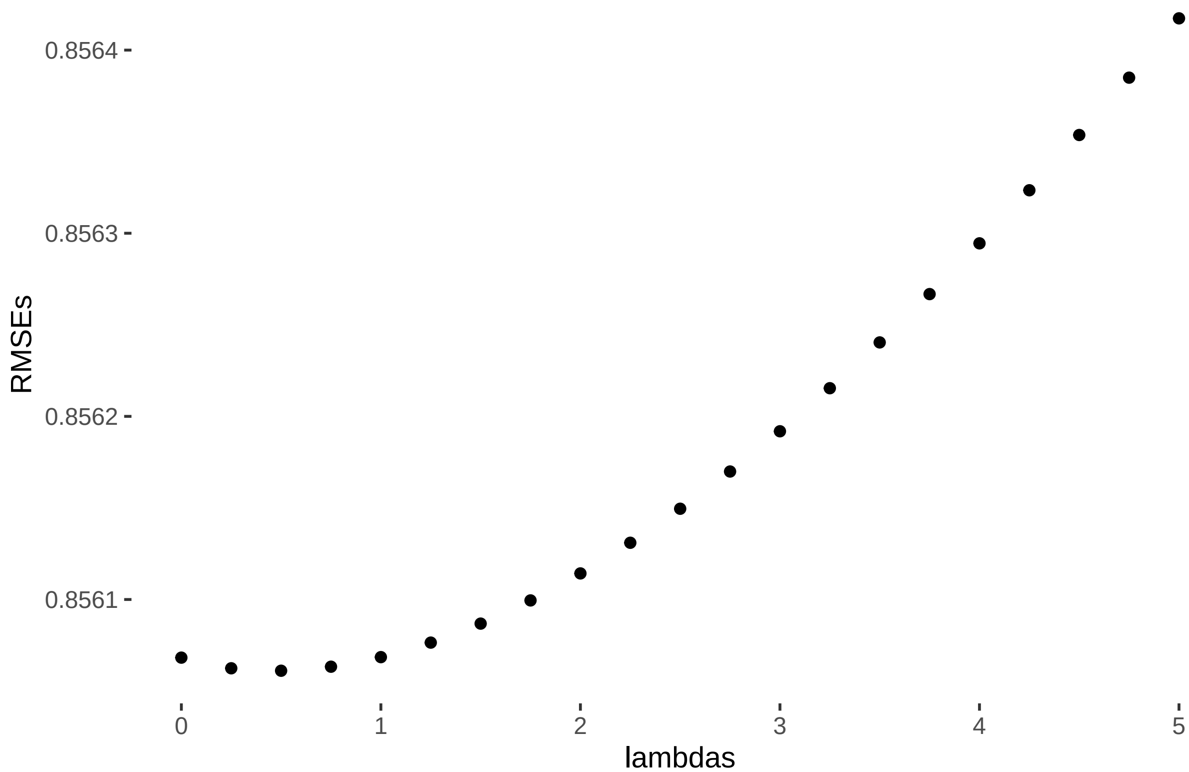
```
    left_join(b_User, by = "userId") %>%
    left_join(b_RYear, by = "year_movie") %>%
    group_by(rate_ts) %>%
    summarise(b_rateTS = sum(rating - mu - b_Movie - b_User - b_RYear)/(n() + l))

  predicts_ratings <- edx %>%
    left_join(b_Movie, by = "movieId") %>%
    left_join(b_User, by = "userId") %>%
    left_join(b_RYear, by = "year_movie") %>%
    left_join(b_rateTS, by = "rate_ts") %>%
    mutate(pred = mu + b_Movie + b_User + b_RYear + b_rateTS) %>%
    pull(pred)

  return(RMSE(predicts_ratings, edx$rating))
})

tibble(lambdas) %>%
  bind_cols(tibble(RMSEs)) %>%
  ggplot(aes(lambdas, RMSEs)) +
  geom_point() +
  theme_update() +
  labs(x = "lambdas", y = "RMSEs") +
  ggtitle("Figure 3.5: RMSE per lambda") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(fill = "white"))
```

Figure 3.5: RMSE per lambda




```
rmse_model5 <- min(RMSEs)
lambda <- lambdas[which.min(RMSEs)]
```

```
## [1] 0.5
```

Implementing λ= 0.5 generates a `RMSE` = 0.8560611. We are now 0.0088389 under our target.

```
rmse_results <- rmse_results %>%
  bind_rows(tibble(Model = "06. Regularized",
                   RMSE = rmse_model5,
                   Goal = ifelse(rmse_model5 < 0.8649, "Under", "Over")))
```

Model	RMSE	Goal
01. Average only	1.0603313	Over
02. Movie Effect	0.9423475	Over
03. +User Effect	0.8567039	Under
04. +RYear Effect	0.8563777	Under
05. +RateTS Effect	0.8560683	Under
06. Regularized	0.8560611	Under

3 Results

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" (Shi, 2020). In order to make this prediction, we have built an ML regularized model that considers four different effects: Movie, User, Release Year & Rate Timestamp.

Until this moment, we have only used our `edx` set, obtaining an `RMSE` of 0.8560611. In this section, we implement the model on the Validation Set.

We start replicating the effects while incorporating the regularized λ.

```r
# Replication with optimal lambda
b_Movie <- edx %>%
  group_by(movieId) %>%
  summarise(b_Movie = sum(rating - mu)/(n() + lambda))

b_User <- edx %>%
  left_join(b_Movie, by = "movieId") %>%
  group_by(userId) %>%
  summarise(b_User = sum(rating - mu - b_Movie)/(n() + lambda))

b_RYear <- edx %>%
  left_join(b_Movie, by = "movieId") %>%
  left_join(b_User, by = "userId") %>%
  group_by(year_movie) %>%
  summarise(b_RYear = sum(rating - mu - b_Movie - b_User)/(n() + lambda))

b_RateTS <- edx %>%
  left_join(b_Movie, by = "movieId") %>%
  left_join(b_User, by = "userId") %>%
  left_join(b_RYear, by = "year_movie") %>%
  group_by(rate_ts) %>%
  summarise(b_rateTS = sum(rating - mu - b_Movie - b_User - b_RYear)/(n() + lambda))
```

Then we calculate the time variables in the `validation` set.

```r
# Validation data arrangement
validation <- validation %>%
  mutate(timestamp = as.POSIXct(timestamp,
                                origin = "1970-01-01",
                                tz = "GMT"),
         year_movie = as.numeric(substr(title,
                                        nchar(title)-4,
                                        nchar(title)-1)),
         year_rated = as.numeric(format(timestamp, "%Y")),
         rate_ts = year_rated - year_movie)
```

Finally we apply the model to the `validation` set.

```r
# Final prediction
predicts_validation <- validation %>%
  left_join(movie_avgs, by = "movieId") %>%
  left_join(user_avgs, by = "userId") %>%
  left_join(RYear_avgs, by = "year_movie") %>%
  left_join(rateTS_avgs, by = "rate_ts") %>%
  mutate(pred = mu + b_rateTS + b_RYear + b_User + b_Movie) %>%
  pull(pred)

rmse_model_final <- RMSE(predicts_validation,
                         validation$rating)
```

We get an `RMSE` = 0.8647026. Because our goal was to generate a model with `RMSE < 0.8649`, we reach an `RMSE` 0.0001974422 under our target.

```r
rmse_results <- rmse_results %>%
  bind_rows(tibble(Model = "07. Validation set",
                   RMSE = rmse_model_final,
                   Goal = ifelse(rmse_model_final < 0.8649, "Under", "Over")))
```

Model	RMSE	Goal
01. Average only	1.0603313	Over
02. Movie Effect	0.9423475	Over
03. +User Effect	0.8567039	Under
04. +RYear Effect	0.8563777	Under
05. +RateTS Effect	0.8560683	Under
06. Regularized	0.8560611	Under
07. Validation set	0.8647026	Under

4 Conclusion

Across this project, we first described the MovieLens 10M dataset while presenting the four variables (two existing, two calculated) we focused on. Then, we did some exploratory data analysis gaining insights for the model. Finally, we developed a recommendation system that considers the effect depending on the movie, the user, the release year, and the rate timestamp. We regularized the effects with a tuning parameter of `0.5`, and got a `RMSE` = 0.8647026 once applied to the Validation Set.

Even if the model reached its goal with a 1.9744224×10^{-4} margin, it still has plenty of opportunity areas to improve on future work:

1. As seen, many top places are occupied by movies with less than five ratings, making the model to consider movie characteristics that are less ranked.

2. The `genres` variable isn't used in this model. Desagregating this column could give more insight for better predictions.

3. Other option is to work on data enrichment, developing APIs to get more characteristics about the movies.

4. GroupLens is constantly improving their sotfware, so downloading bigger and more recent databases could give more insights for predictions.

5. Meng (2020) and other bloggers constantly publish more advanced ML techniques that are able to refine the analysis.

5 References

- Harper, F.M. & Konstan, J.A. (2015). "The MovieLens Datasets: History and Context". ACM Transactions on Interactive Intelligent Systems: University of Minnesota. Available in: https://dl.acm.org/doi/10.1145/2827872

- Irizarry, R. A. (2020). "Introduction to Data Science: Data Analysis and Prediction Algorithms with R". Available in: https://rafalab.github.io/dsbook/

- Meng, M. (2020). "Movie Recommendation System based on MovieLens: Leveraged Natural Language Processing (NLP) and Computer Vision (CV)". Towards Data Science. Available in: https://towardsdatascience.com/movie-recommendation-system-based-on-movielens-ef0df580cd0e

- Shi, W. (2020). "Recommendation Systems: A Review". Towards Data Science. Available in: https://towardsdatascience.com/recommendation-systems-a-review-d4592b6caf4b

6 Appendix

```
sessionInfo()
```

```
## R version 4.0.3 (2020-10-10)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 19041)
##
## Matrix products: default
##
## Random number generation:
##  RNG:     Mersenne-Twister
##  Normal:  Inversion
##  Sample:  Rounding
##
## locale:
## [1] LC_COLLATE=English_United States.1252
```

```
## [2] LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] knitr_1.30        data.table_1.13.2 caret_6.0-86      lattice_0.20-41
##  [5] forcats_0.5.0     stringr_1.4.0     dplyr_1.0.2       purrr_0.3.4
##  [9] readr_1.4.0       tidyr_1.1.2       tibble_3.0.4      ggplot2_3.3.2
## [13] tidyverse_1.3.0
##
## loaded via a namespace (and not attached):
##  [1] httr_1.4.2           jsonlite_1.7.1       splines_4.0.3
##  [4] foreach_1.5.1        prodlim_2019.11.13   modelr_0.1.8
##  [7] assertthat_0.2.1     highr_0.8            stats4_4.0.3
## [10] cellranger_1.1.0     yaml_2.2.1           ipred_0.9-9
## [13] pillar_1.4.7         backports_1.2.0      glue_1.4.2
## [16] pROC_1.16.2          digest_0.6.27        rvest_0.3.6
## [19] colorspace_2.0-0     recipes_0.1.15       htmltools_0.5.0
## [22] Matrix_1.2-18        plyr_1.8.6           timeDate_3043.102
## [25] pkgconfig_2.0.3      broom_0.7.2          haven_2.3.1
## [28] scales_1.1.1         gower_0.2.2          lava_1.6.8.1
## [31] farver_2.0.3         generics_0.1.0       ellipsis_0.3.1
## [34] withr_2.3.0          nnet_7.3-14          cli_2.2.0
## [37] survival_3.2-7       magrittr_2.0.1       crayon_1.3.4
## [40] readxl_1.3.1         evaluate_0.14        fs_1.5.0
## [43] fansi_0.4.1          nlme_3.1-150         MASS_7.3-53
## [46] xml2_1.3.2           class_7.3-17         tools_4.0.3
## [49] hms_0.5.3            lifecycle_0.2.0      munsell_0.5.0
## [52] reprex_0.3.0         compiler_4.0.3       rlang_0.4.9
## [55] grid_4.0.3           iterators_1.0.13     rstudioapi_0.13
## [58] labeling_0.4.2       rmarkdown_2.5        gtable_0.3.0
## [61] ModelMetrics_1.2.2.2 codetools_0.2-18     DBI_1.1.0
## [64] reshape2_1.4.4       R6_2.5.0             lubridate_1.7.9.2
## [67] utf8_1.1.4           stringi_1.5.3        Rcpp_1.0.5
## [70] vctrs_0.3.5          rpart_4.1-15         dbplyr_2.0.0
## [73] tidyselect_1.1.0     xfun_0.19
```