Project

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```
# This project is related to the MovieLens Project of the HarvardX: Data Science: Capstone course.
# Create edx set, validation set, and submission file
# Loading required package: tidyverse and package caret
if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: tidyverse
```

```
## Warning: package 'tidyverse' was built under R version 4.0.3
```

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

```
## v ggplot2 3.3.2     v purrr   0.3.4
## v tibble  3.0.3     v dplyr   1.0.2
## v tidyr   1.1.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
```

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

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

```
## Loading required package: caret
```

```
## Warning: package 'caret' was built under R version 4.0.3
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

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

```r
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")

# To predict the movie rating of the users that haven't seen the movie yet, the dataset will be splitte
# The Validation subset will contain the 10% of the MovieLens data.
set.seed(1)
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, list = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]

# UserId and movieId in validation set are also in edx subset:
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)
```

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

```r
edx <- rbind(edx, removed)
rm(dl, ratings, movies, test_index, temp, movielens, removed)

# Get started!
# Look the first rows of "edx" subset as below and relative summary
head(edx) %>%
  print.data.frame()
```

```
##   userId movieId rating timestamp title genres
## 1      1     122      5 838985046  <NA>   <NA>
## 2      1     185      5 838983525  <NA>   <NA>
## 3      1     231      5 838983392  <NA>   <NA>
## 4      1     292      5 838983421  <NA>   <NA>
## 5      1     316      5 838983392  <NA>   <NA>
## 6      1     329      5 838983392  <NA>   <NA>
```

```r
summary(edx)
```

```
##      userId         movieId          rating        timestamp
##  Min.   :    1   Min.   :    1   Min.   :0.500   Min.   :7.897e+08
##  1st Qu.:18122   1st Qu.:  648   1st Qu.:3.000   1st Qu.:9.468e+08
##  Median :35743   Median : 1834   Median :4.000   Median :1.035e+09
##  Mean   :35869   Mean   : 4120   Mean   :3.512   Mean   :1.033e+09
##  3rd Qu.:53602   3rd Qu.: 3624   3rd Qu.:4.000   3rd Qu.:1.127e+09
##  Max.   :71567   Max.   :65133   Max.   :5.000   Max.   :1.231e+09
##     title              genres
##  Length:9000061     Length:9000061
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##
```

```
# The total of unique movies and users in the edx subset is about 70.000 unique users and about 10.700
edx %>%
  summarize(n_users = n_distinct(userId),
            n_movies = n_distinct(movieId))
```

```
##   n_users n_movies
## 1   69878    10677
```

```
# The RMSE is our measure of model accuracy.We can interpret the RMSE similarly to a standard deviation
RMSE <- function(true_ratings, predicted_ratings){
  sqrt(mean((true_ratings - predicted_ratings)^2))
}

# The first basic model predicts the same rating for all movies, so we compute the dataset's mean ratin
mu <- mean(edx$rating)
mu
```

```
## [1] 3.512464
```

```
# If we predict all unknown ratings, we obtain the first naive RMSE
naive_rmse <- RMSE(validation$rating, mu)
naive_rmse
```

```
## [1] 1.060651
```

```
# This is the results
rmse_results <- data_frame(method = "Average movie rating model", RMSE = naive_rmse)
```

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

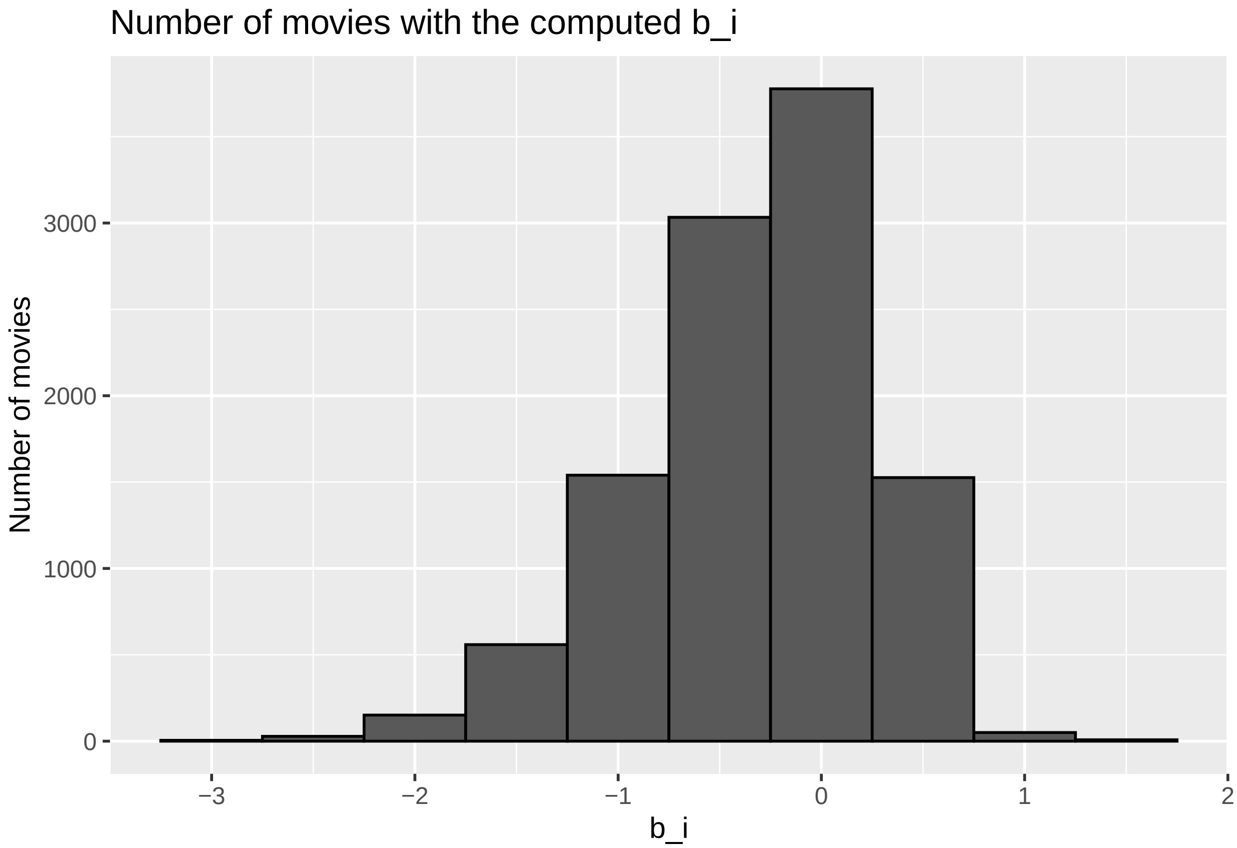
```
rmse_results %>% knitr::kable()
```

method	RMSE
Average movie rating model	1.060651

```r
# Movie effect model
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu))
```

```
## 'summarise()' ungrouping output (override with '.groups' argument)
```

```r
movie_avgs %>% qplot(b_i, geom ="histogram", bins = 10, data = ., color = I("black"),
                     ylab = "Number of movies", main = "Number of movies with the computed b_i")
```



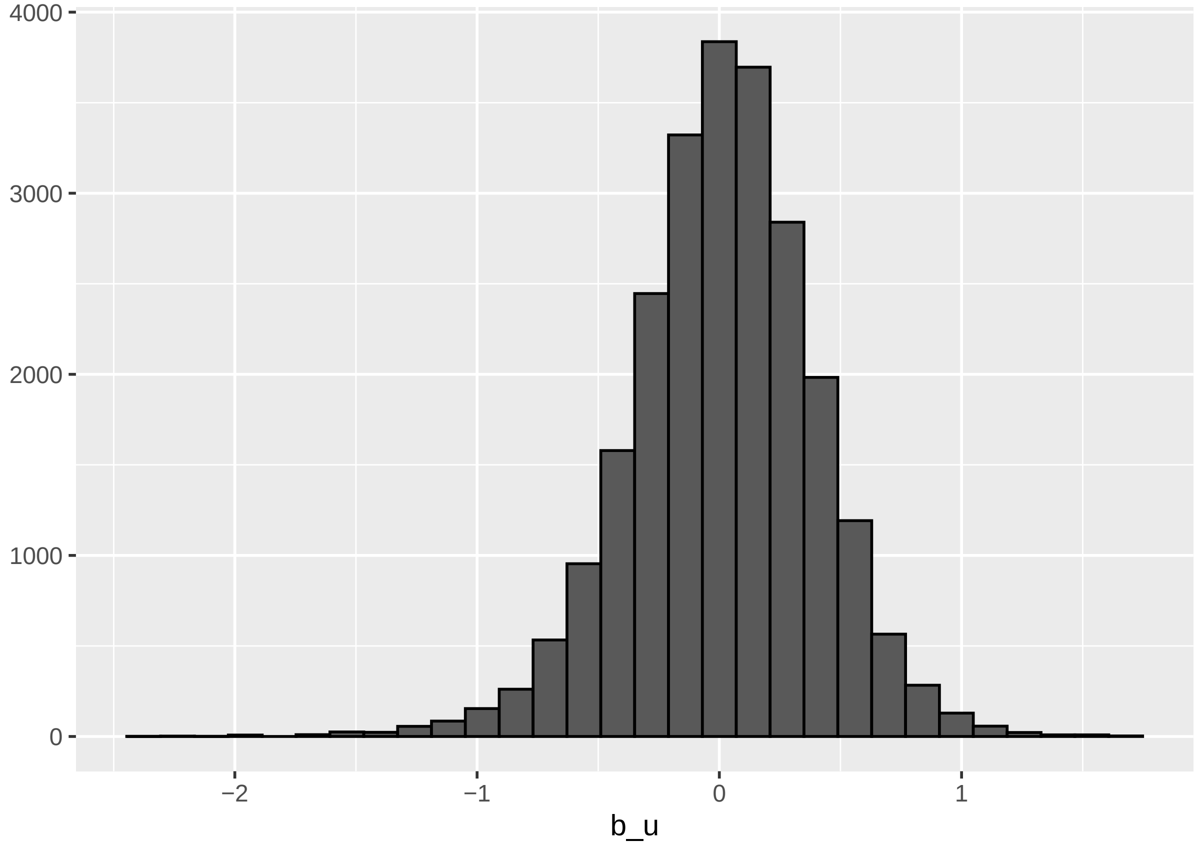
```r
# Our prediction improve once we predict using this model
predicted_ratings <- mu +  validation %>%
  left_join(movie_avgs, by='movieId') %>%
  pull(b_i)
model_1_rmse <- RMSE(predicted_ratings, validation$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie effect model",
                                     RMSE = model_1_rmse ))
rmse_results %>% knitr::kable()
```

method	RMSE
Average movie rating model	1.0606506
Movie effect model	0.9437046

```
# We compute the average rating
user_avgs<- edx %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  filter(n() >= 100) %>%
  summarize(b_u = mean(rating - mu - b_i))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
user_avgs%>% qplot(b_u, geom ="histogram", bins = 30, data = ., color = I("black"))
```



```
# We compute an approximation
user_avgs <- edx %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u = mean(rating - mu - b_i))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
# The construct predictors and see RMSE improves
predicted_ratings <- validation%>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  mutate(pred = mu + b_i + b_u) %>%
  pull(pred)
model_2_rmse <- RMSE(predicted_ratings, validation$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie and user effect model",
                                     RMSE = model_2_rmse))
rmse_results %>% knitr::kable()
```

method	RMSE
Average movie rating model	1.0606506
Movie effect model	0.9437046
Movie and user effect model	0.8655329

```
# Regularized movie and user effect model
lambdas <- seq(0, 10, 0.25)
rmses <- sapply(lambdas, function(l){

  mu <- mean(edx$rating)

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

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

```
## ‘summarise()‘ ungrouping output (override with ‘.groups‘ argument)

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## `summarise()` ungrouping output (override with `.groups` argument)
```
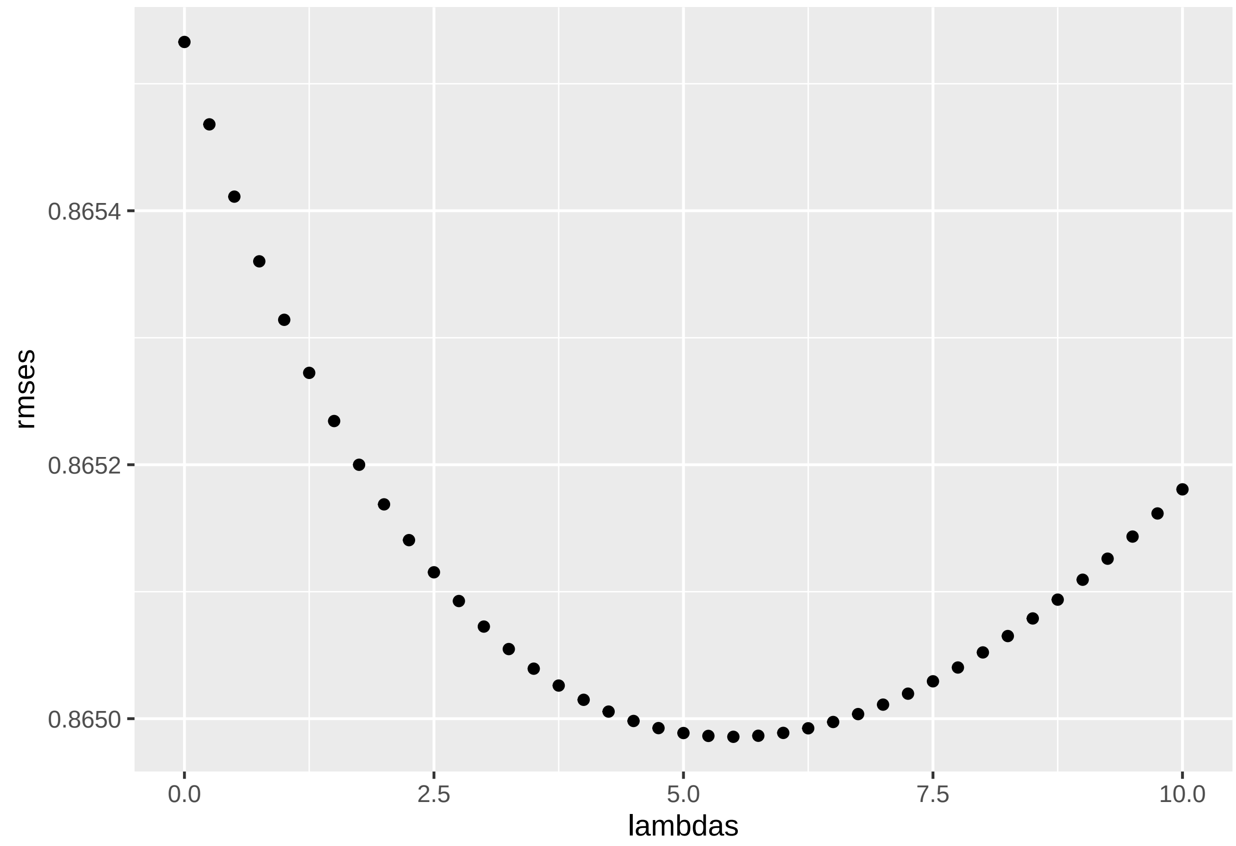

```r
# We plot RMSE vs lambdas to select the optimal lambda
qplot(lambdas, rmses)
```



```r
# For the full model, the optimal lambda is this
lambda <- lambdas[which.min(rmses)]
lambda
```

```
## [1] 5.5
```

```r
# The new results
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Regularized movie and user effect model",
                                     RMSE = min(rmses)))
rmse_results %>% knitr::kable()
```

method	RMSE
Average movie rating model	1.0606506
Movie effect model	0.9437046
Movie and user effect model	0.8655329
Regularized movie and user effect model	0.8649857

```r
# The RMSE values of all the represented models are these
rmse_results %>% knitr::kable()
```

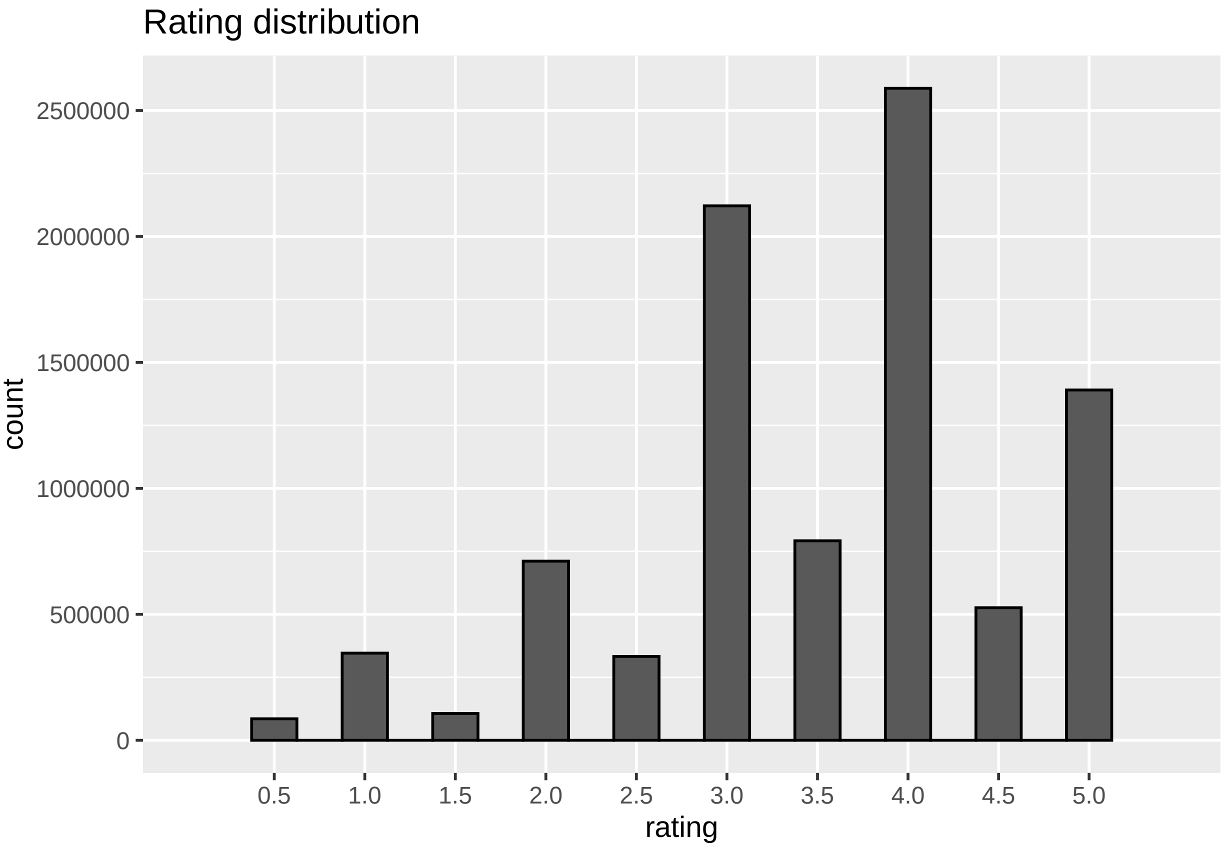
method	RMSE
Average movie rating model	1.0606506
Movie effect model	0.9437046
Movie and user effect model	0.8655329
Regularized movie and user effect model	0.8649857

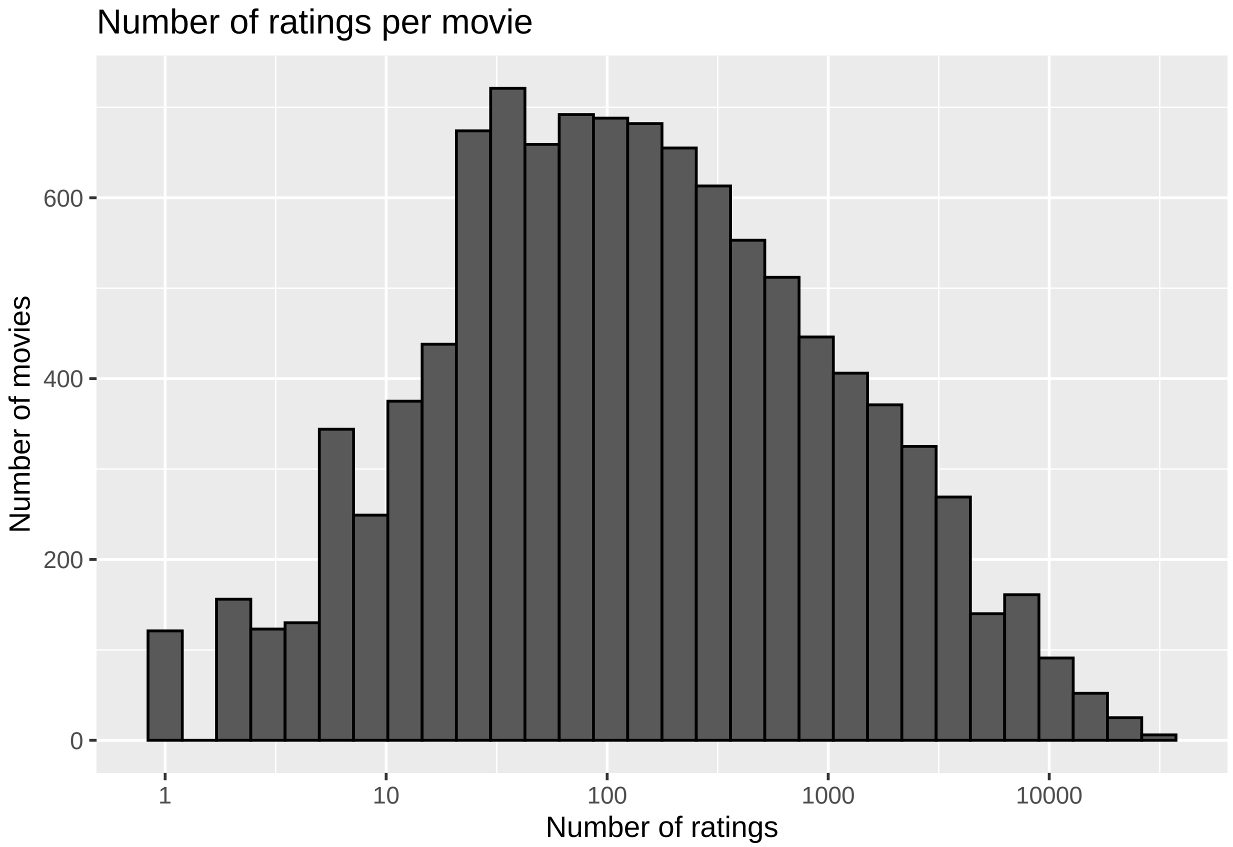
```r
# Conclusion
# We can affirm to have built a machine learning algorithm to predict movie ratings with MovieLens data
```

Including Plots

You can also embed plots, for example:

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

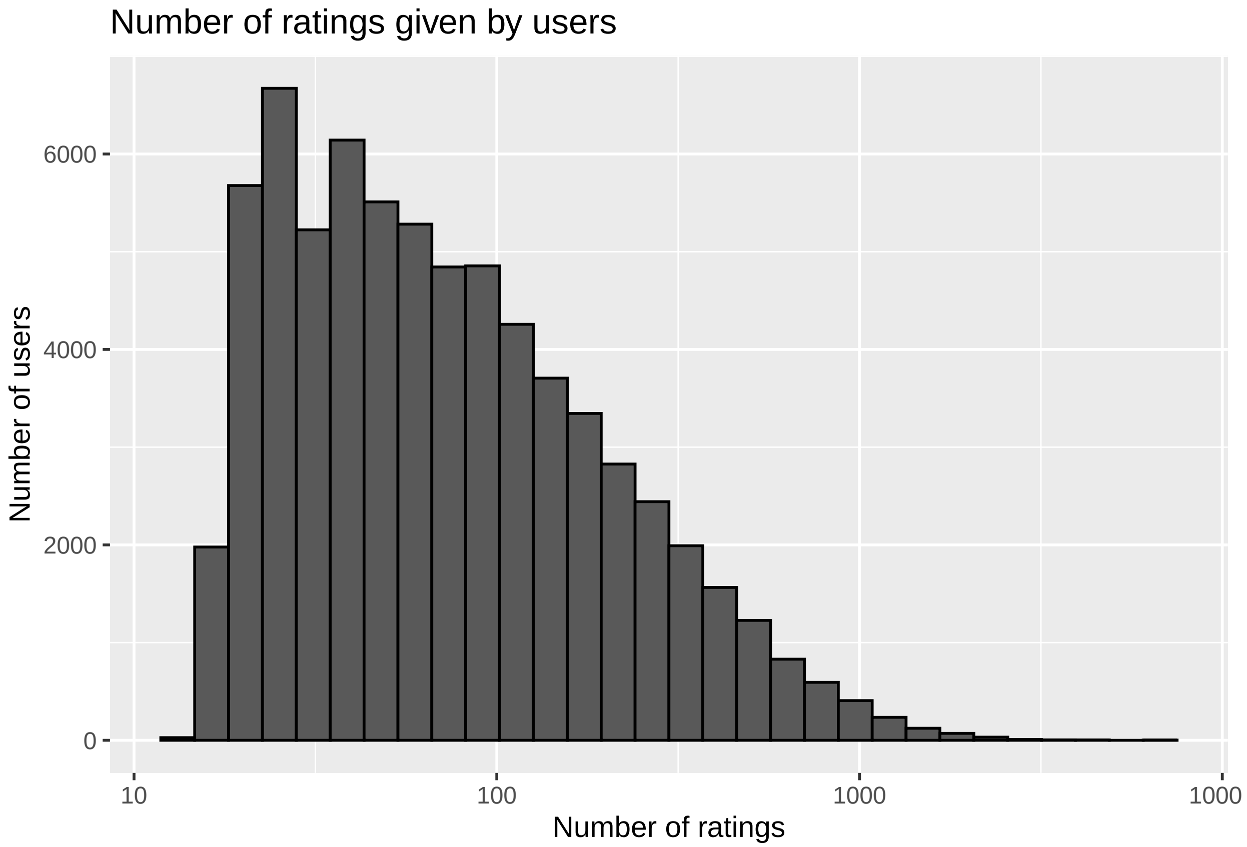

Rating distribution
count
2500000
2000000
1500000
1000000
500000
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
rating



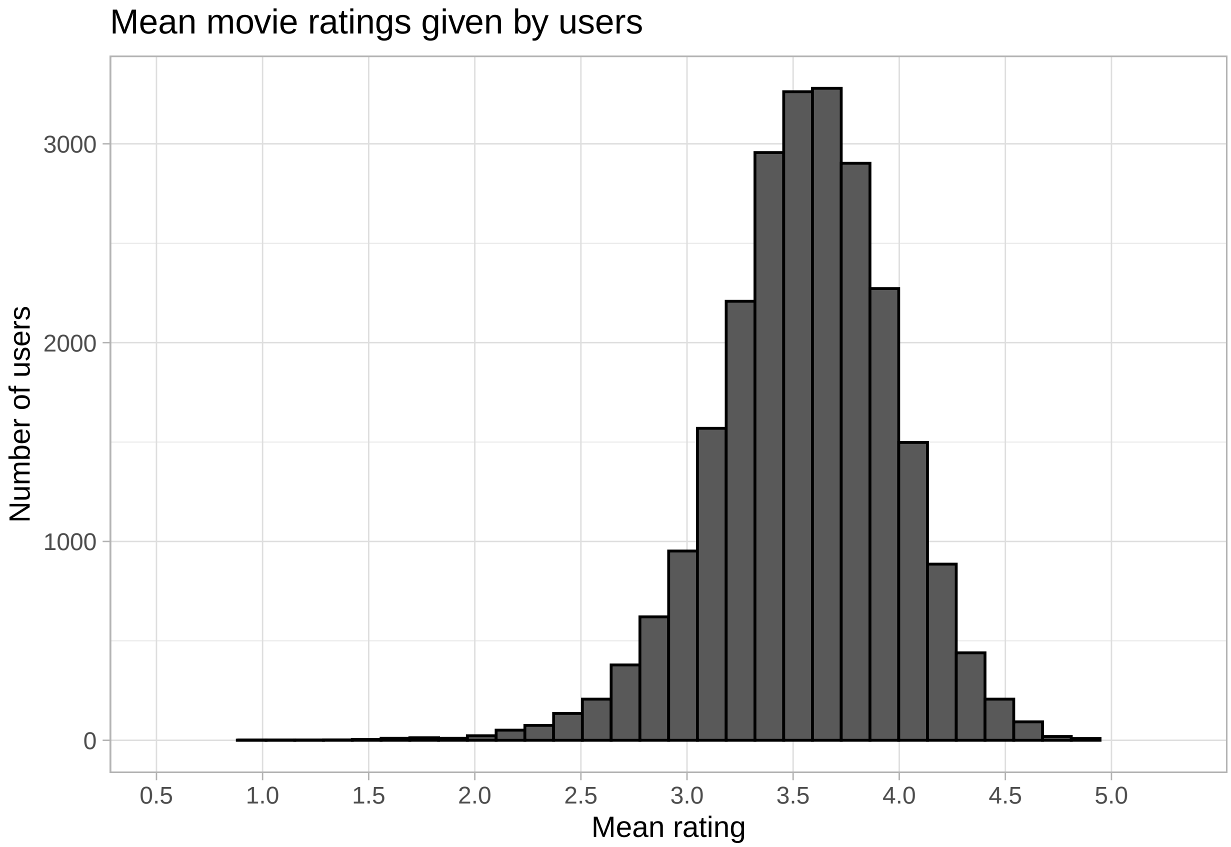
```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## `summarise()` regrouping output by 'title' (override with `.groups` argument)
```

title	rating	n_rating
NA	5.0	1
NA	3.0	1
NA	3.0	1
NA	1.0	1
NA	3.0	1
NA	1.0	1
NA	1.0	1
NA	2.0	1
NA	1.5	1
NA	2.0	1
NA	1.5	1
NA	1.0	1
NA	3.0	1
NA	3.0	1
NA	3.0	1
NA	2.5	1
NA	2.5	1
NA	3.0	1
NA	4.5	1
NA	2.5	1



```
## ‘summarise()‘ ungrouping output (override with ‘.groups‘ argument)

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



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.