HarvardX - Data Science Capstone: MovieLens Project

1. Introduction

Recommendation systems use historic ratings of products/services by users to make specific recommendations. They are based on ratings' predictions. Previous ratings from a given user are used to predict what rating he/she would give to a specific item and items for which a high rating is predicted are then recommended to that user.

Many organizations such as Amazon and Netflix use recommendation systems to predict how many stars a user would give a specific item. One star suggests they don't like the item, whereas five stars suggests they love it.

In this project, we will build our movie recommendation system where we will predict ratings for a set of users whose actual ratings are hidden. We check the performance of our predictions against two metrics RMSE and Accuracy.

Important Note: Running the code of this project could mobilize the full resources of your machine and the process could take several hours to complete. The code has been validated on an i7 CPU with 16 GB RAM machine and Jupyterlab version 0.35.3 for macOS 10.14.2.

2. Data

The MovieLens dataset that we are using for this project is provided by GroupLens, a research lab in the Department of Computer Science and Engineering at the University of Minnesota.

GroupLens has collected and made available rating datasets from their website (https://grouplens.org/datasets/movielens/ (https://grouplens.org/datasets/movielens/)). The datasets were collected over various periods of time, depending on the size of the set.

- **MovieLens 100K Dataset (size 5 MB)**

  Stable benchmark dataset. 100,000 ratings from 1,000 users on 1,700 movies. Released 4/1998.
- **MovieLens 1M Dataset (size 6 MB)**

  Stable benchmark dataset. 1 million ratings from 6,000 users on 4,000 movies. Released 2/2003.
- **MovieLens 10M Dataset (size 63 MB)**

Stable benchmark dataset. 10 million ratings and 100,000 tag applications applied to 10,000 movies by 72,000 users. Released 1/2009.

- **MovieLens 20M Dataset (size 190 MB)**

  Stable benchmark dataset. 20 million ratings and 465,000 tag applications applied to 27,000 movies by 138,000 users. Includes tag genome data with 12 million relevance scores across 1,100 tags. Released 4/2015 - updated 10/2016.
- **MovieLens Tag Genome Dataset (size 41MB)**

  11 million computed tag-movie relevance scores from a pool of 1,100 tags applied to 10,000 movies. Released 3/2014.

  The tag genome is a data structure that encodes how strongly movies exhibit particular properties represented by tags (atmospheric, thought-provoking, realistic, etc.)

  This dataset contains the tag relevance values that make up the tag genome. Tag relevance represents the relevance of a tag to a movie on a continuous scale from 0 to 1.

  Note the MovieLens 20M also contains (more recent) tag genome data.

For this project, we are using the **MovieLens 10M** dataset.

In this dataset, users were selected at random from the online movie recommender service MovieLens. Users selected had rated at least 20 movies. No demographic information is included. each user is represented by an Id, and no further information is provided. The data are contained in 3 files:

- **movies.dat**

  Movie information is contained in this file. Each line represents one movie and has the following format MovieID::Title::Genres.
  - MovieID is the MovieLens id.
  - Movie titles include year of release. They are entered manually, so errors and inconsistencies may exist.
  - Genres are pipe-separated list and are selected from the following:
    - Action
    - Adventure
    - Animation
    - Children
    - Comedy
    - Crime
    - Documentary
    - Drama
    - Fantasy
    - Film-Noir
    - Horror
    - IMAX
    - Musical
    - Mystery
    - Romance
    - Sci-Fi
    - Thriller

- War
- Western

- **ratings.dat**

  All ratings are contained in this file. Each line of this file represents one rating of one movie by one user, and has the following format UserID::MovieID::Rating::Timestamp.
  - The lines within this file are ordered first by UserID, then, within user, by MovieID.
  - Ratings are made on a 5-star scale, with half-star increments.
  - Timestamps represent the time of rating in seconds since midnight UTC of January 1, 1970.

- **tags.dat**

  All tags are contained in this file. Each line represents one tag applied to one movie by one user, and has the following format UserID::MovieID::Tag::Timestamp.
  - The lines within this file are ordered first by UserID, then, within user, by MovieID.
  - Tags are user generated metadata about movies. Each tag is typically a single word, or short phrase. The meaning, value and purpose of a particular tag is determined by each user.
  - Timestamps represent the time of tagging in seconds since midnight UTC of January 1, 1970.

  Note: For the sake of simplicity, we do not use this tags file for our project.

3. Methodology

3.1 Create subsets for the project

We want to create two subsets as follows:

- edx dataset, which contains 90% of the MovieLens 10M "ratings" and "movies" files, merged by the MovieID feature. This dataset is used for building our ratings prediction system.
- validation dataset, which is the remaining 10%, with UserID and MovieID features, for the purpose of validation of our model. We ensure that UserID and MovieID in the validation set are also in the edx dataset.

3.2 Exploratory Analysis

In this section, we explore data in four main directions:

1. Initial exploration of the edx dataset.
2. Exploring users.

    - Users' activity per year
    - Users' rating characteristics

1. Exploring movies.

    - Most reviewed movies and most popular movies
    - Movies by year of release
    - Movies by genre

1. Exploring ratings.

    - Distribution of ratings
    - How do the ratings distributions compare before and after half-star scores are allowed?
    - Ratings per year

3.3 Predictive Model

In this section, we will go through several methods to build our predictive model in order to achieve the lowest RMSE and best accuracy we can. We will keep track of the RMSE for each method and report the overall RMSE and accuracy at the end.

Our approach is inspired by the 2006 Netflix challenge (https://www.netflixprize.com/assets/GrandPrize2009_BPC_BellKor.pdf (https://www.netflixprize.com/assets/GrandPrize2009_BPC_BellKor.pdf)), where we will blend the techniques of user and movie effects, regularization and matrix factorization / Principal Components Analysis. Finally, we will use a naive Bayes approach to classify our predicted ratings into categories going from 0.5 star to 5 stars rating with incremental of 0.5 star so that we can evaluate the accuracy of our predictions against true ratings.

The used methods are as follows:

1. User and movie effects with regularization.
2. Matrix factorization.
3. Naive Bayes.

4. Results and Discussion

Create subsets for the project

In [1]:
```
# --- CREATE EDX SET -----------------------------------------
# Note: This process could take several minutes

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")

# 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 <- 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.da
t")), "\\::", 3)
colnames(movies) <- c("movieId", "title", "genres")
movies <- as.data.frame(movies) %>% mutate(movieId = as.numeric(lev
els(movieId))[movieId],
                                           title = as.character(tit
le),
                                           genres = as.character(ge
nres))

movielens <- left_join(ratings, movies, by = "movieId")
```

```
Loading required package: tidyverse
── Attaching packages ─────────────────────────────────────── tidy
verse 1.2.1 ──
✔ ggplot2 3.0.0     ✔ purrr   0.2.5
✔ tibble  1.4.2     ✔ dplyr   0.7.6
✔ tidyr   0.8.1     ✔ stringr 1.3.1
✔ readr   1.1.1     ✔ forcats 0.3.0
── Conflicts ──────────────────────────────────────── tidyverse_
conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
Loading required package: caret
Loading required package: lattice

Attaching package: 'caret'

The following object is masked from 'package:purrr':

    lift
```

In [2]:

```
# --- NOTE: Updated 1/18/2019 -------------------------------

# --- VALIDATION SET WILL BE 10% OF 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,]

# Make sure userId and movieId in validation set are also in edx se
t

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)

# Clean up memory by deleting unused objects and performing a garb
age collection
rm(dl, ratings, movies, test_index, temp, movielens, removed)
gc()
```

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

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11502484	614.3	19138902	1022.2	25437946	1358.6
Vcells	91112456	695.2	250410368	1910.5	282223611	2153.2

Exploratory Analysis

In [3]:
```
# --- USED LIBRARIES ---------------------------------------

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

```
Loading required package: lubridate

Attaching package: ‘lubridate’

The following object is masked from ‘package:base’:

    date

Loading required package: gridExtra

Attaching package: ‘gridExtra’

The following object is masked from ‘package:dplyr’:

    combine
```

In [4]:
```
# --- INITIAL EXPLORATION OF THE EDX DATASET ----------------

# Dimensions of the edx dataset

head(edx)

cat("The edx dataset has", nrow(edx), "rows and", ncol(edx), "colum
ns.\n")
cat("There are", n_distinct(edx$userId), "different users and", n_d
istinct(edx$movieId), "different movies in the edx dataset.")
```

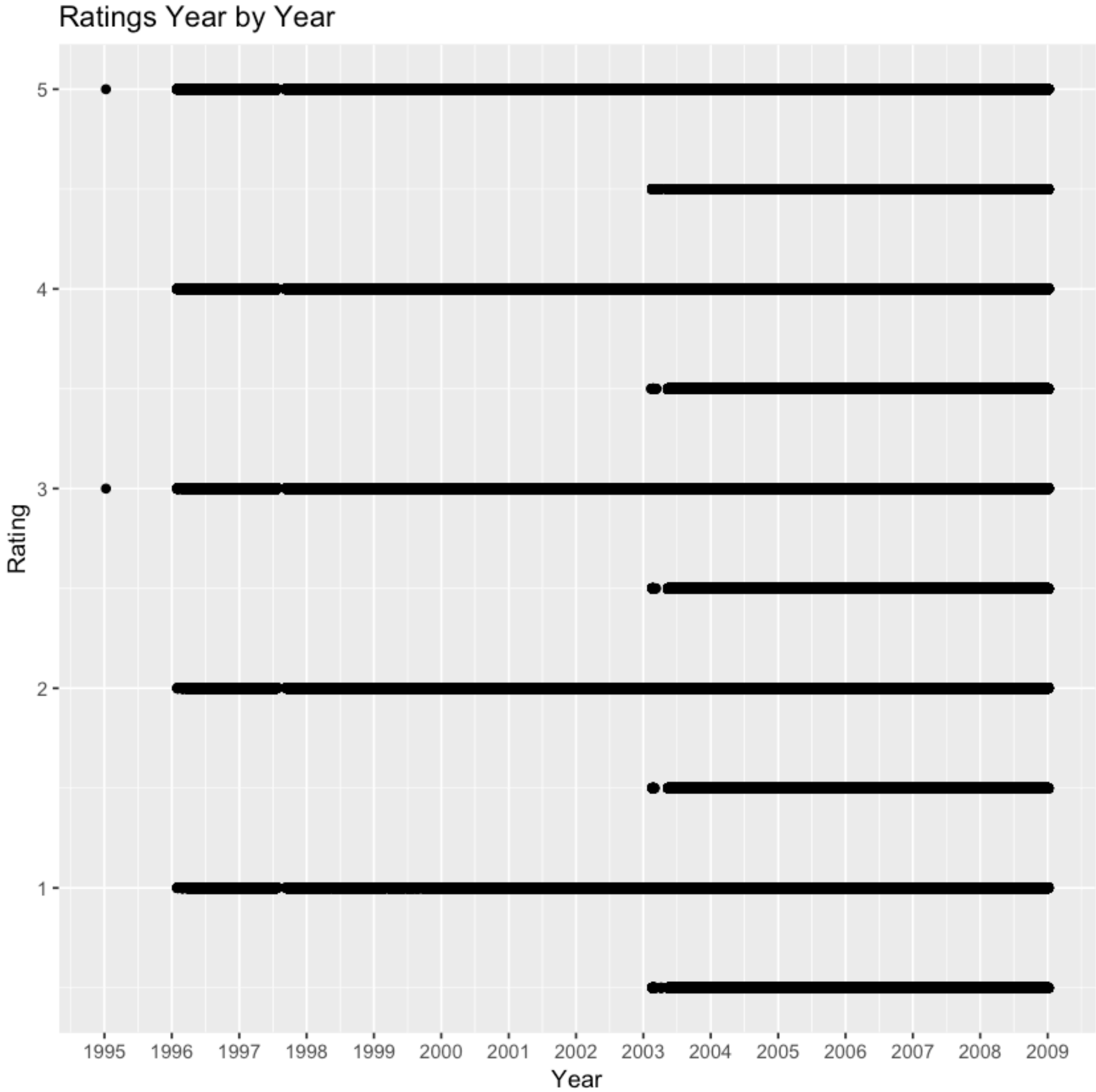
	userId	movieId	rating	timestamp	title	genres
1	1	122	5	838985046	Boomerang (1992)	Comedy|Romance
2	1	185	5	838983525	Net, The (1995)	Action|Crime|Thriller
4	1	292	5	838983421	Outbreak (1995)	Action|Drama|Sci-Fi|Thriller
5	1	316	5	838983392	Stargate (1994)	Action|Adventure|Sci-Fi
6	1	329	5	838983392	Star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

```
The edx dataset has 9000055 rows and 6 columns.
There are 69878 different users and 10677 different movies in the
edx dataset.
```

In [5]:
```
# Check if edx has missing values
any(is.na(edx))
```

FALSE

In [6]:
```
# What are the ratings year by year?
# Note: This process could take several minutes

edx_year_rating <- edx %>%
    transform (date = as.Date(as.POSIXlt(timestamp, origin = "1970-01-01", format = "%Y-%m-%d"), format = "%Y-%m-%d")) %>%
    mutate (year_month = format(as.Date(date), "%Y-%m"))

ggplot(edx_year_rating) +
    geom_point(aes(x = date, y = rating)) +
    scale_x_date(date_labels = "%Y", date_breaks  = "1 year") +
    labs(title = "Ratings Year by Year", x = "Year", y = "Rating")
```

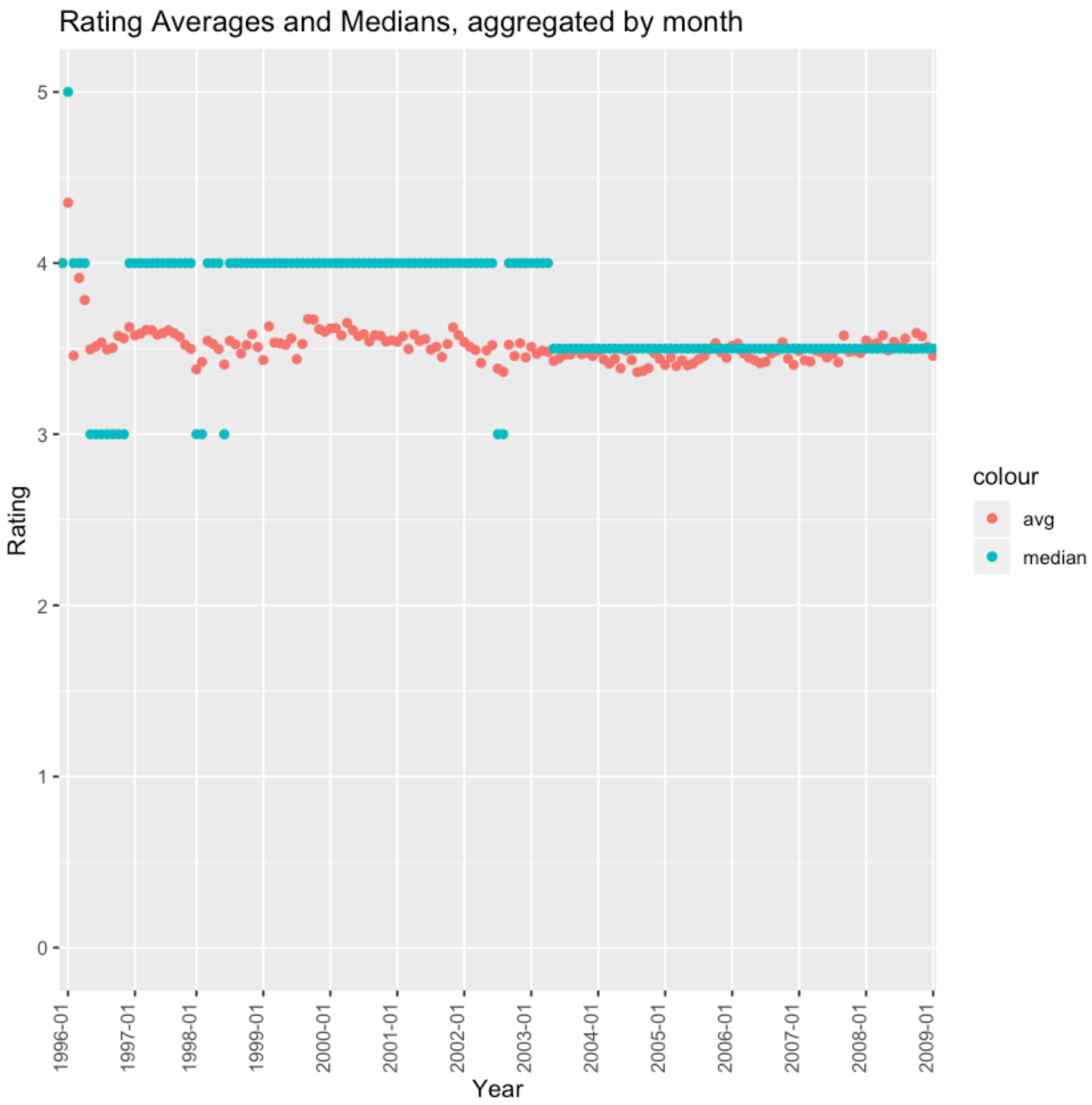


We have only one rating in 1995 and more interestingly, no half-star rating was provided before 2003.

Let's keep in mind that the MovieLens datasets were collected over various periods of time and specifically, the MovieLens 1M dataset was released in February 2003. The MovieLens 10M dataset was released in January 2009.

Further investigation confirms that the half-star rating had been implemented from 18 February 2003.

In [7]:
```
# What are the rating averages and medians year by year?

edx_yearmonth_rating <- edx_year_rating %>%
    group_by(year_month) %>%
    summarize(avg = mean(rating), median = median(rating))

ggplot(edx_yearmonth_rating) +
    geom_point(aes(x = year_month, y = avg, colour = "avg")) +
    geom_point(aes(x = year_month, y = median, colour = "median"))
+
    ylim(0, 5) +
    scale_x_discrete(breaks = c("1996-01", "1997-01", "1997-01", "1
998-01", "1999-01",
                                "2000-01", "2001-01", "2002-01", "2
003-01", "2004-01",
                                "2005-01", "2006-01", "2007-01", "2
008-01", "2009-01")) +
    theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust =
0)) +
    labs(title = "Rating Averages and Medians, aggregated by month
", x = "Year", y = "Rating")
```



Only one month (January) record for 1995.

While the rating averages are rather consistent over the whole dataset, the medians are distributed between 3 and 4 stars until beginning of 2003 and changed to 3.5 stars afterwards.

We may also note that the distribution of averages looks noisier between 1998 and 2000.

In [8]:
```
# Clean up memory
rm(edx_year_rating, edx_yearmonth_rating)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11598778	619.5	19138902	1022.2	25437946	1358.6
Vcells	91300710	696.6	415744300	3171.9	518721523	3957.6

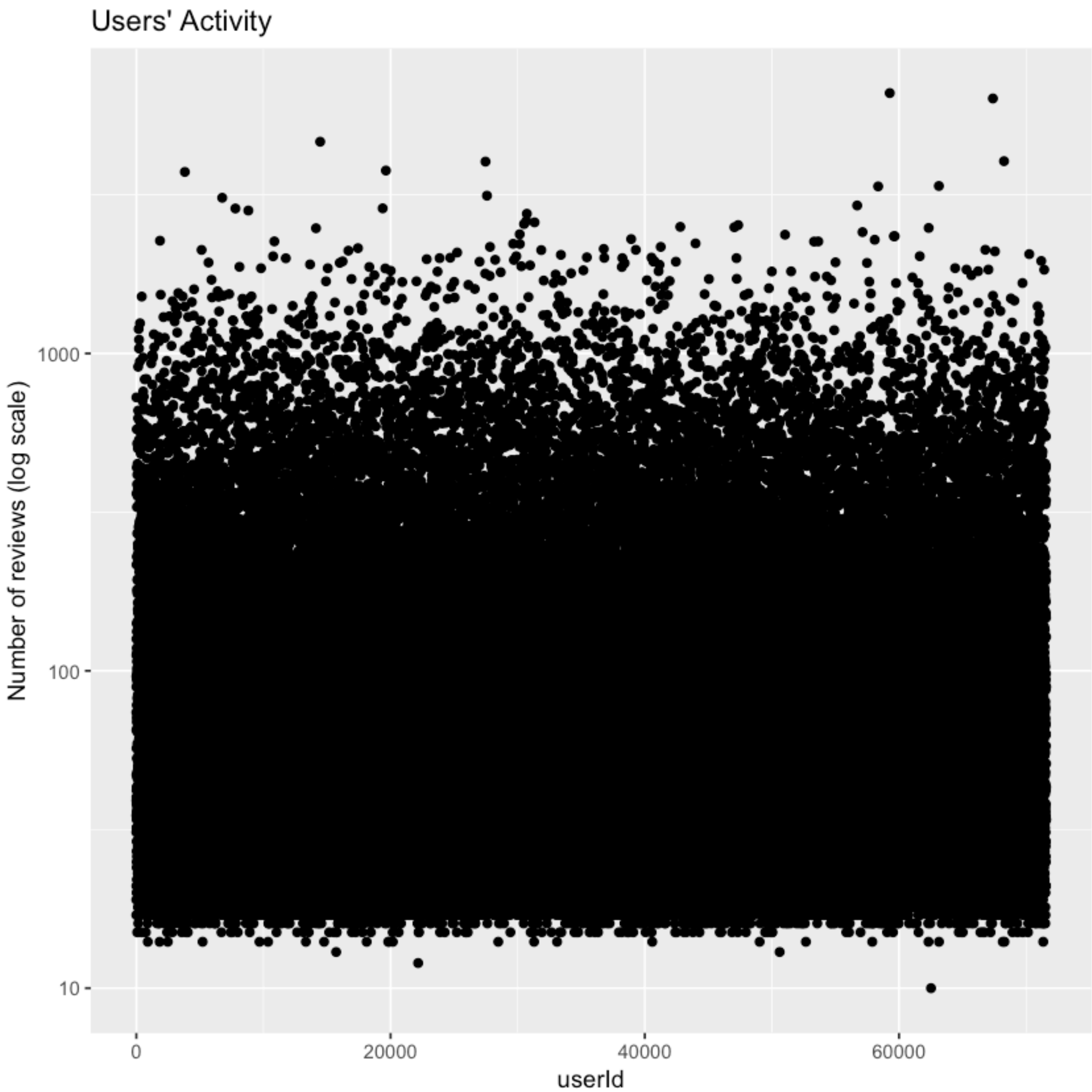
In [9]:
```
# --- EXPLORING USERS ---------------------------------------

edx_users <- edx %>%
    group_by(userId) %>%
    summarize(count = n()) %>%
    arrange(desc(count))

summary(edx_users$count)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   10.0    32.0    62.0   128.8   141.0  6616.0
```

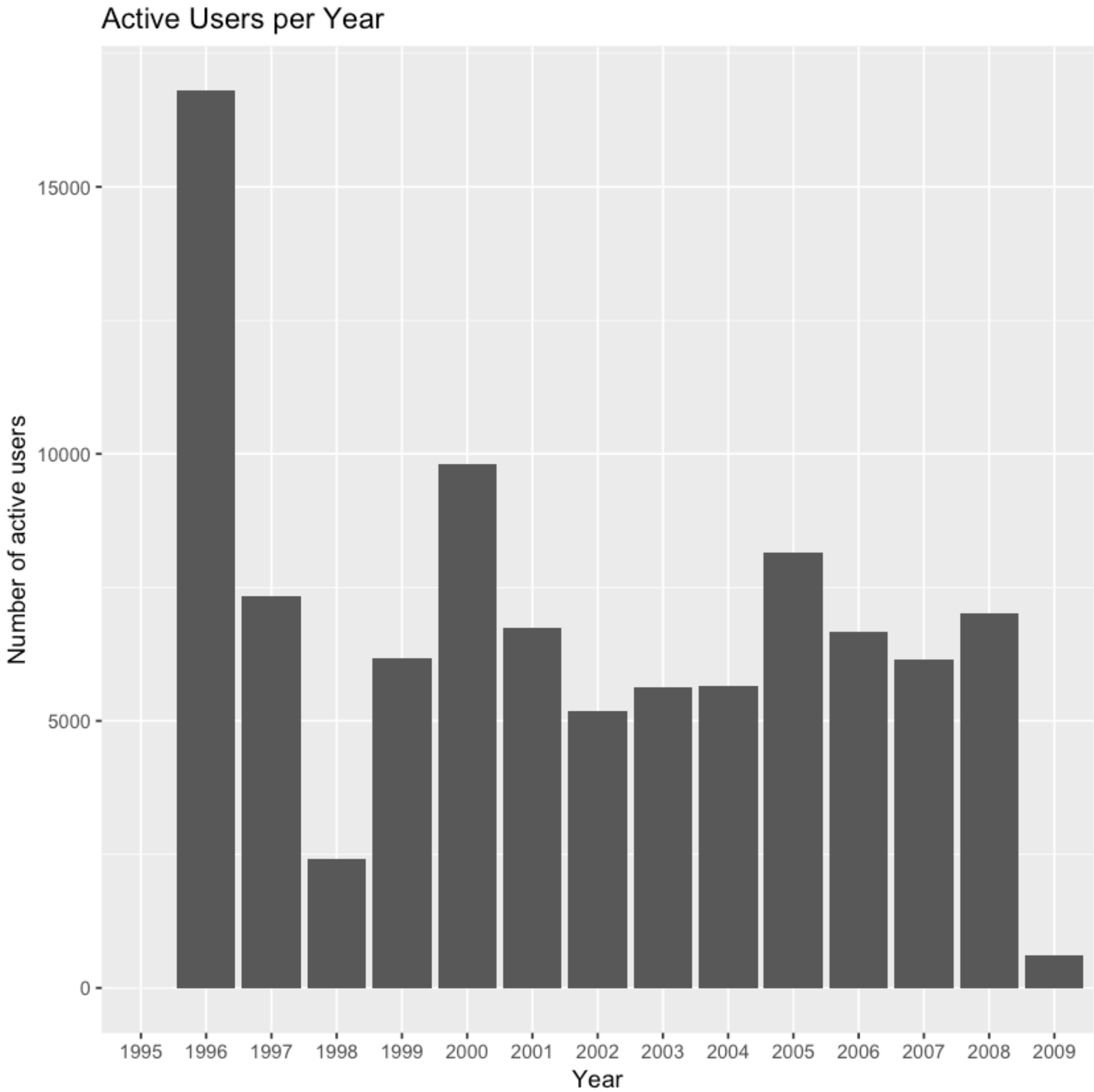
In [10]:
```
cat("The most active user(s) rated", max(edx_users$count), "movies
and the least active user(s) rated", min(edx_users$count), "movies.
\n")
cat("In average, an user rated about", round(mean(edx_users$count))
, "movies, and the median is", median(edx_users$count), "movies.")
```

```
The most active user(s) rated 6616 movies and the least active use
r(s) rated 10 movies.
In average, an user rated about 129 movies, and the median is 62 m
ovies.
```

In [11]:
```
ggplot(edx_users) +
        geom_point(aes(x = userId, y = count)) +
        scale_y_log10() +
        labs(title = "Users' Activity", x = "userId", y = "Number o
f reviews (log scale)")
```



In [12]:
```
# How many active users do we have per year?

users_year <- edx %>%
    transform(timestamp = format(as.POSIXlt(timestamp, origin = "19
70-01-01"), "%Y")) %>%
    select(timestamp, userId) %>%
    group_by(timestamp) %>%
    summarise(count = n_distinct(userId))

ggplot(data = users_year, aes(x = timestamp, y = count)) +
    geom_bar(stat = "identity") +
    labs(title = "Active Users per Year", x = "Year", y = "Number o
f active users")
```



1996 is the year with the largest number of active users and 1998 the year with the smallest number (less than 2,500 active users). 1995 and 2009 are not full years.

In [13]:
```
# How many reviews do we have for the most active users?

user_year_rating <-edx %>%
    transform(timestamp = format(as.POSIXlt(timestamp, origin = "19
70-01-01"), "%Y")) %>%
    group_by(timestamp, userId) %>%
    summarise(count = n()) %>%
    arrange(desc(count))

summary(user_year_rating$count)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   1.00   26.00   51.00   95.42  110.00 4648.00 
```

There is one user who rated 4,648 movies in a year. What a commitment!

In [14]:
```
# Let's see further about high counts of reviews given

head(user_year_rating)
```

timestamp	userId	count
2002	14463	4648
2007	67385	4233
2002	7795	2799
2006	3817	2731
2001	59269	2610
2007	58357	2588

Some users provided a very large number of reviews in a year. For example, userId 14463 rated 4,648 movies in 2002 (only). This, by the way, confirms that the timestamp is the time when the movie is rated, not when it is watched.

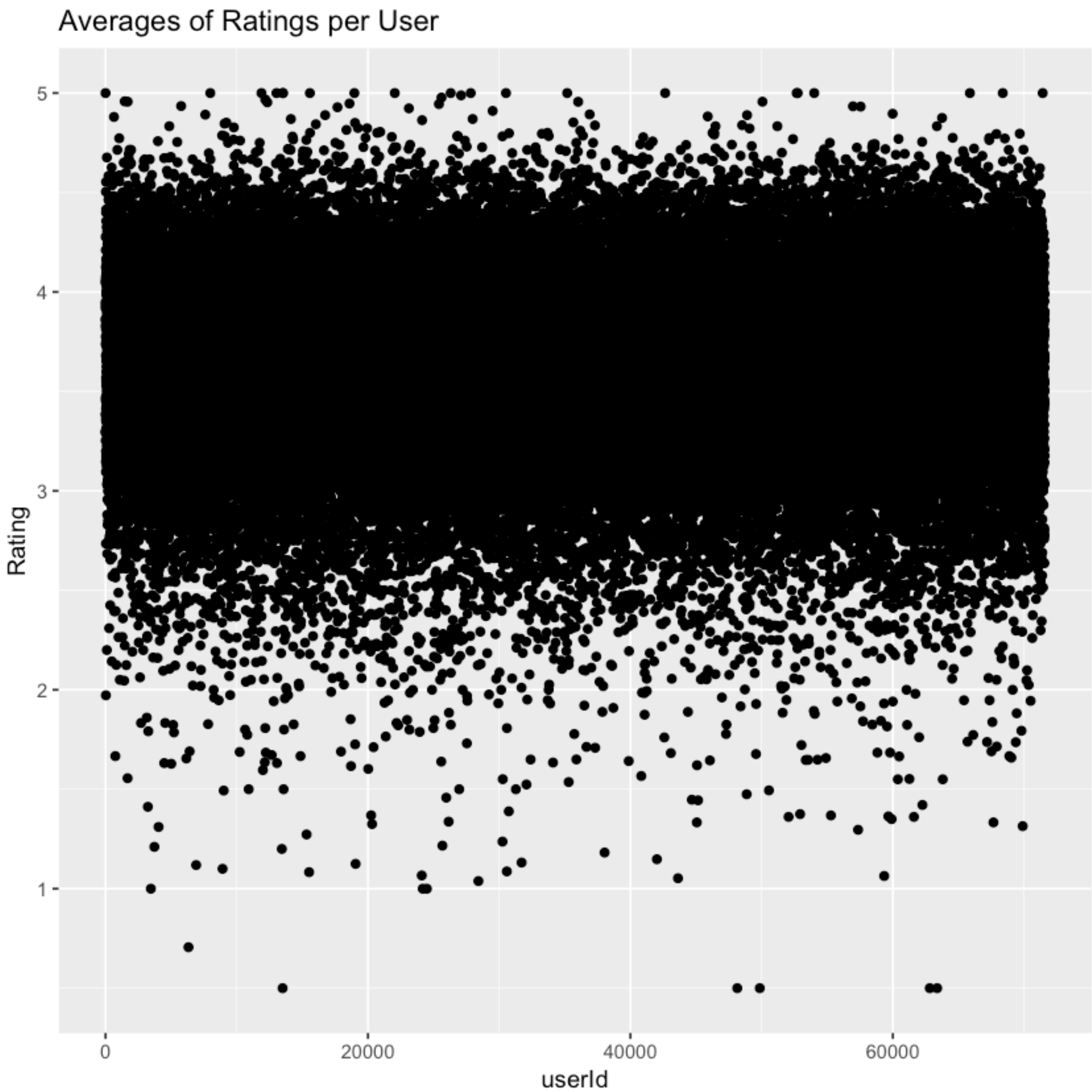
In [15]:
```
# Let's see further about userId 14463.

userId_14463 <- edx %>%
    filter(userId == 14463) %>%
    summarize(count = n(), avg = mean(rating), median = median(rati
ng), std = sd(rating), max = max(rating), min = min(rating))

userId_14463
```

count	avg	median	std	max	min
4648	2.403614	2	0.688186	5	1

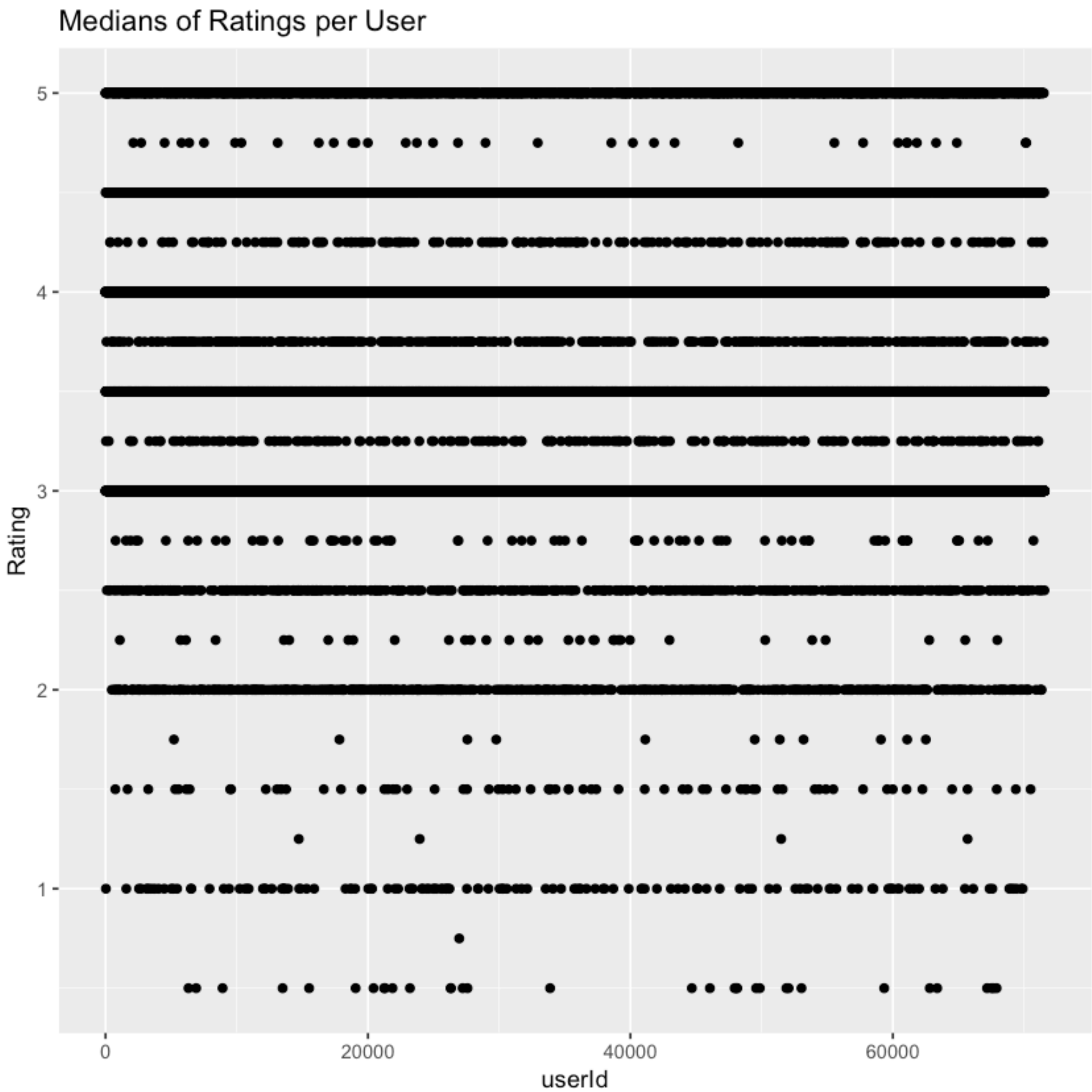
With a median rating of 2 stars, userId 14463 didn't like much the movies he/she rated.

In [16]:
```
# --- Users' rating characteristics ------------------------

users_rating_char <- edx %>%
    group_by(userId) %>%
    summarize(count = n(), avg = mean(rating), median = median(rati
ng), std = sd(rating)) %>%
    arrange(desc(count))
```

In [17]:
```
# What are the averages of ratings per user?
ggplot(users_rating_char) +
    geom_point(aes(x = userId, y = avg)) +
    labs(title = "Averages of Ratings per User", x = "userId", y =
"Rating")
```

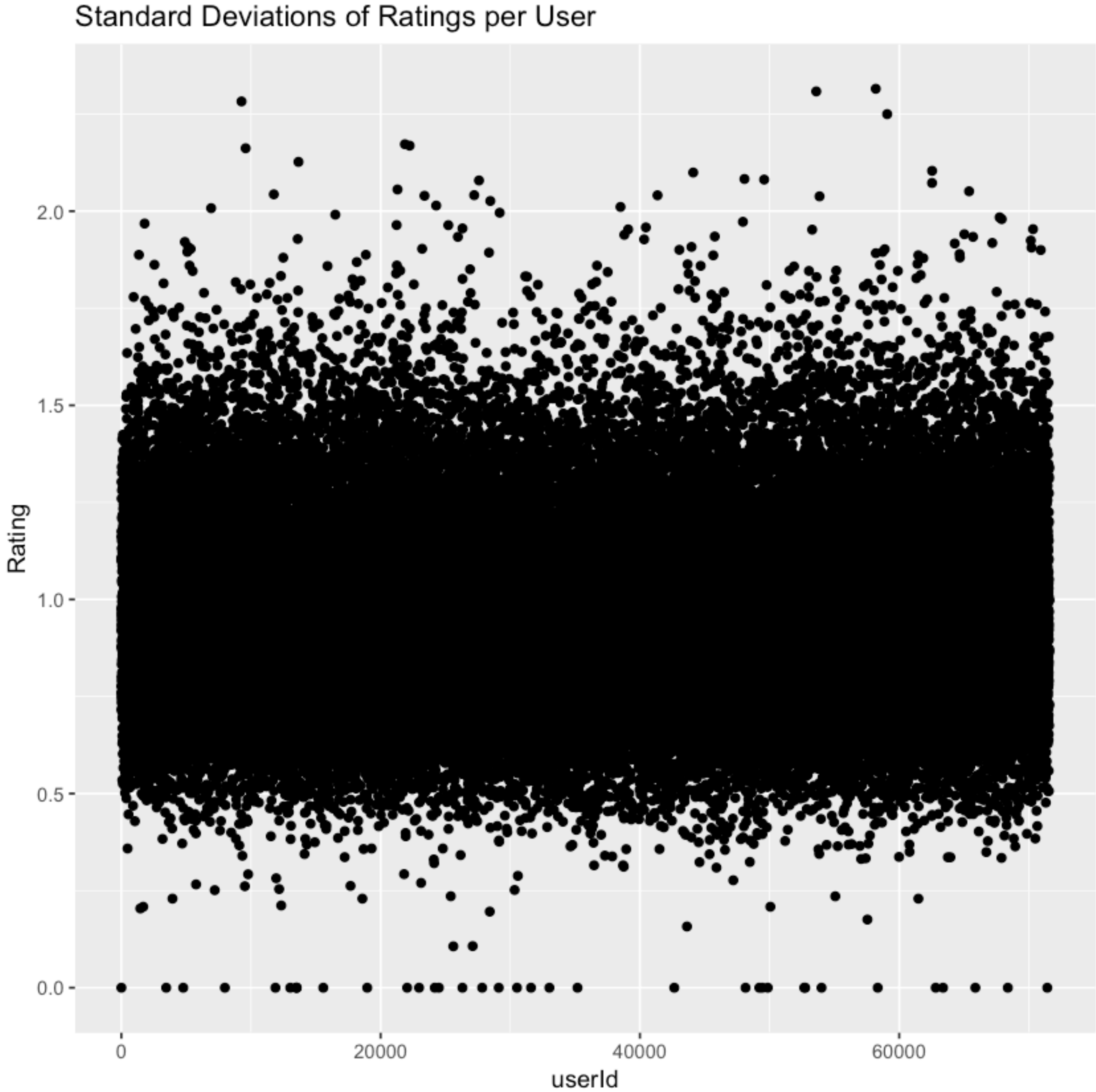


In [18]:
```
# What are the medians of ratings per user?
ggplot(users_rating_char) +
    geom_point(aes(x = userId, y = median)) +
    labs(title = "Medians of Ratings per User ", x = "userId", y =
"Rating")
```



Looking at the medians distribution, we may note that half-star ratings are less common than whole star ratings as before February 2003, the system didn't allow half-star scoring.

In [19]:
```
# What are the standard deviations of ratings per user?
ggplot(users_rating_char) +
    geom_point(aes(x = userId, y = std)) +
    labs(title = "Standard Deviations of Ratings per User", x = "us
erId", y = "Rating")
```



We may note that some users always rated movies with the same score (standard deviation with zero value) while the vast majority clearly have preferences with a standard deviation ranging between 0.5 and 1.5 stars. **It shows interactions between users and movies.**

In [20]:
```
# Clean up memory
rm(edx_users, users_year, user_year_rating, userId_14463, users_rat
ing_char)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11612830	620.2	19138902	1022.2	25437946	1358.6
Vcells	91607360	699.0	332595440	2537.6	518721523	3957.6

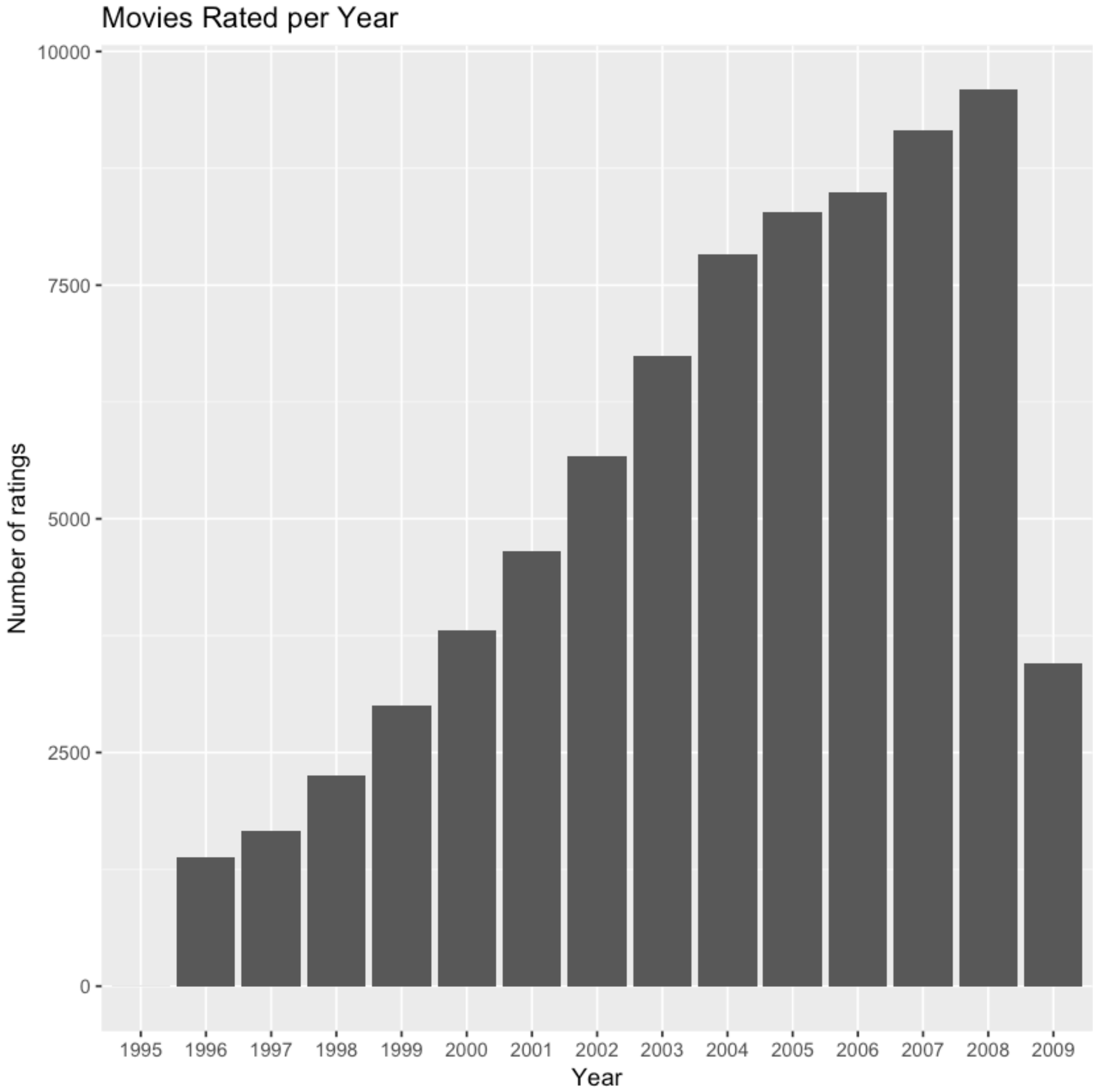
In [21]:
```
# --- EXPLORING MOVIES ---------------------------------------

edx_movies <- edx %>%
    group_by(movieId) %>%
    summarize(count = n()) %>%
    arrange(desc(count))

summary(edx_movies$count)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    1.0    30.0   122.0   842.9   565.0 31362.0
```

In [22]:
```
cat("The most reviewed movie(s) was(were) rated by", max(edx_movies
$count), "users and the least reviewed one(s) was(were) rated by",
min(edx_movies$count), "user.\n")
cat("A movie, in average, is rated about", round(mean(edx_movies$co
unt)), "times, and the median is", median(edx_movies$count), "ratin
gs.")
```

```
The most reviewed movie(s) was(were) rated by 31362 users and the
least reviewed one(s) was(were) rated by 1 user.
A movie, in average, is rated about 843 times, and the median is 1
22 ratings.
```

In [23]:
```
# How many movies are rated per year?

movies_year <- edx %>%
    transform(timestamp = format(as.POSIXlt(timestamp, origin = "19
70-01-01"), "%Y")) %>%
    select(timestamp, movieId) %>%
    group_by(timestamp) %>%
    summarise(count = n_distinct(movieId))

ggplot(data = movies_year, aes(x = timestamp, y = count)) +
    geom_bar(stat = "identity") +
    labs(title = "Movies Rated per Year", x = "Year", y = "Number o
f ratings")
```



Not surprisingly, we can see a clear growth of ratings, regardless of the number of active users, as more movies are referenced and available for review.

In [24]:
```
# What are the most reviewed movies?
movies_votes <- edx %>%
    group_by(movieId, title) %>%
    summarize(count = n()) %>%
    arrange(desc(count))

head(movies_votes)
```

movieId	title	count
296	Pulp Fiction (1994)	31362
356	Forrest Gump (1994)	31079
593	Silence of the Lambs, The (1991)	30382
480	Jurassic Park (1993)	29360
318	Shawshank Redemption, The (1994)	28015
110	Braveheart (1995)	26212

Pulp Fiction, **Forest Gump**, and **The Silence of the Lambs** are the three most reviewed movies.

In [25]:
```
# What are the most popular movies?

# Best movies (by ratings average and with a minimum of 1,000 ratin
gs)
top_movies <- edx %>%
    group_by(movieId, title) %>%
    filter(n() >= 1000) %>%
    summarise(count = n(), avg = mean(rating), median = median(rati
ng), min = min(rating), max = max(rating)) %>%
    arrange(desc(avg))

head(top_movies)
```

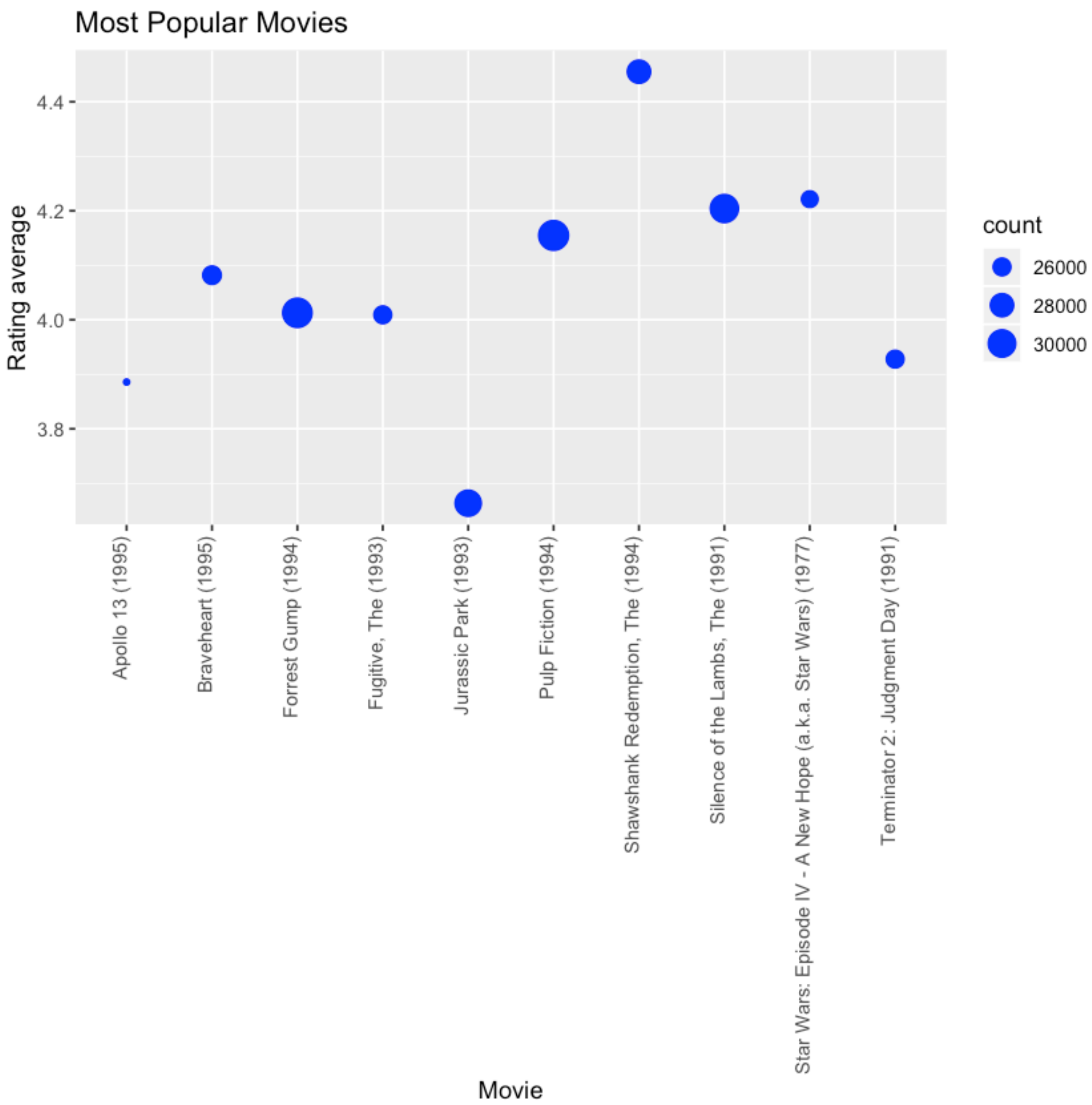
movieId	title	count	avg	median	min	max
318	Shawshank Redemption, The (1994)	28015	4.455131	5.0	0.5	5
858	Godfather, The (1972)	17747	4.415366	5.0	0.5	5
50	Usual Suspects, The (1995)	21648	4.365854	4.5	0.5	5
527	Schindler's List (1993)	23193	4.363493	4.5	0.5	5
912	Casablanca (1942)	11232	4.320424	4.5	0.5	5
904	Rear Window (1954)	7935	4.318652	4.5	0.5	5

We note a high variation in these counts of reviews, e.g. **The Shawshank Redemption** has about 10,000 more reviews than **The Godfather** (28,015 reviews vs 17,747 reviews, respectively).

So when we sort by average score, the ranking will be "polluted" by movies with low count of reviews. To deal with this issue we can use a weighted average as used on the IMDB website for their Top 250 ranking. To take this bias into account, we can use the weighted rating as follows:

In [26]:
```
# R = average of the movie ratings
# v = number of ratings for the movie
# m = minimum ratings required to be listed in the Top movies
# C = the mean rating across the whole dataset

wr <- function(R, v, m, C) {
  return (v/(v+m))*R + (m/(v+m))*C
}

new_top_movies <- edx %>%
    group_by(movieId, title) %>%
    summarise(count = n(), avg = mean(rating)) %>%
    mutate(weighted_rating = wr(avg, count, 1000, mean(avg))) %>%
    arrange(desc(weighted_rating))
```

In [27]:
```
# Top 10 popular movies

top10_movies <- new_top_movies %>% select(movieId, title, count, av
g) %>% head(10)

ggplot(data = top10_movies, aes(x = title, y = avg)) +
    geom_point(aes(size = count),color = "blue") +
    theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust=0
)) +
    labs(title = "Most Popular Movies", x = "Movie", y = "Rating av
erage")
```



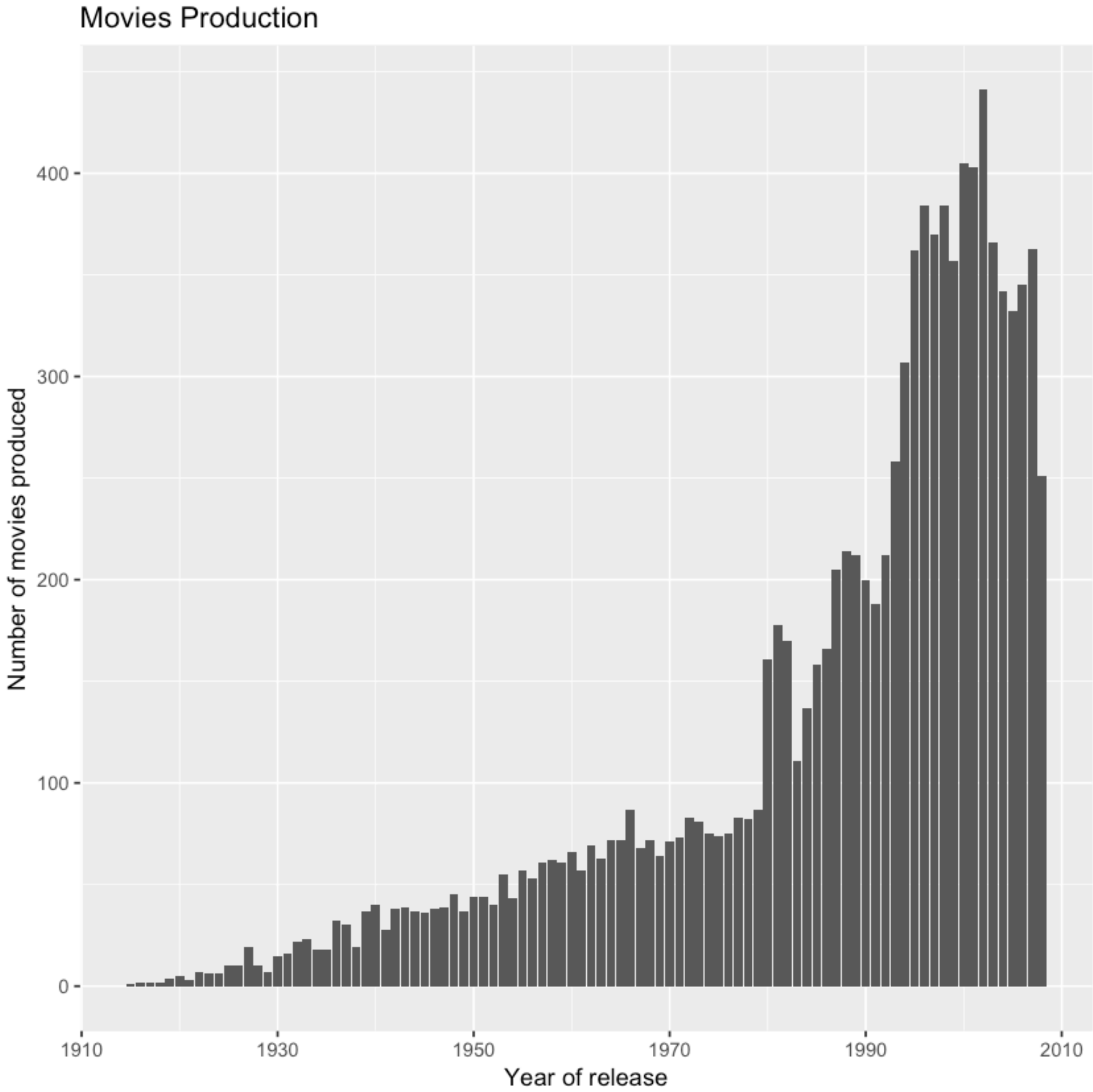
If we consider popularity as the quality of being liked by a large number of people, we want to consider movies that are highly rated by a large number of users.

In [28]:
```
head(new_top_movies, 10)
```

movieId	title	count	avg	weighted_rating
296	Pulp Fiction (1994)	31362	4.154789	0.9690996
356	Forrest Gump (1994)	31079	4.012822	0.9688270
593	Silence of the Lambs, The (1991)	30382	4.204101	0.9681346
480	Jurassic Park (1993)	29360	3.663522	0.9670619
318	Shawshank Redemption, The (1994)	28015	4.455131	0.9655351
110	Braveheart (1995)	26212	4.081852	0.9632515
457	Fugitive, The (1993)	25998	4.009155	0.9629602
589	Terminator 2: Judgment Day (1991)	25984	3.927859	0.9629410
260	Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977)	25672	4.221311	0.9625075
150	Apollo 13 (1995)	24284	3.885789	0.9604493

Pulp Fiction, **Forrest Gump**, and **The Silence of the Lambs** are the 3 most popular movies.

In [29]:
```
# How many movies are produced per year?

# Extract the year of release from the movie title
title_year <- edx %>%
  mutate(title = str_trim(title)) %>% # trim whitespaces
  extract(title, c("title", "year"), regex = "^(.*) \\(([0-9 \\-]*)
\\)$", remove = T, convert = T) # split title to title, year

# Number of movies produced per year
movies_title_year <- title_year %>%
    select(year, movieId) %>%
    group_by(year) %>%
    summarise(count = n_distinct(movieId)) %>%
    arrange(desc(count))

ggplot(data = movies_title_year, aes(x = year, y = count)) +
            geom_bar(stat = "identity") +
            labs(title = "Movies Production", x = "Year of release"
, y = "Number of movies produced")
```



In our data, we can see an exponential growth until 2002 and then a trend drop. The latter could be caused by the fact that the data is collected until 2009 (not a full year) so we have less new movies referenced in the dataset. As for the former, maybe it is somewhat linked to the beginning of the Internet era, implying a growing popularity of the demand for movies online.

In [30]:
```
# What are the most rated movie genres?
# Note: This process could take several minutes

movies_genre <- edx %>%
    separate_rows(genres, sep = "\\|")

genres_ratings <- movies_genre %>% # Separate the combined genre ca
tegories into single genres
    group_by(genres) %>%
    summarise(count = n()) %>%
    arrange(desc(count))

genres_ratings
```

genres	count
Drama	3910127
Comedy	3540930
Action	2560545
Thriller	2325899
Adventure	1908892
Romance	1712100
Sci-Fi	1341183
Crime	1327715
Fantasy	925637
Children	737994
Horror	691485
Mystery	568332
War	511147
Animation	467168
Musical	433080
Western	189394
Film-Noir	118541
Documentary	93066
IMAX	8181
(no genres listed)	7

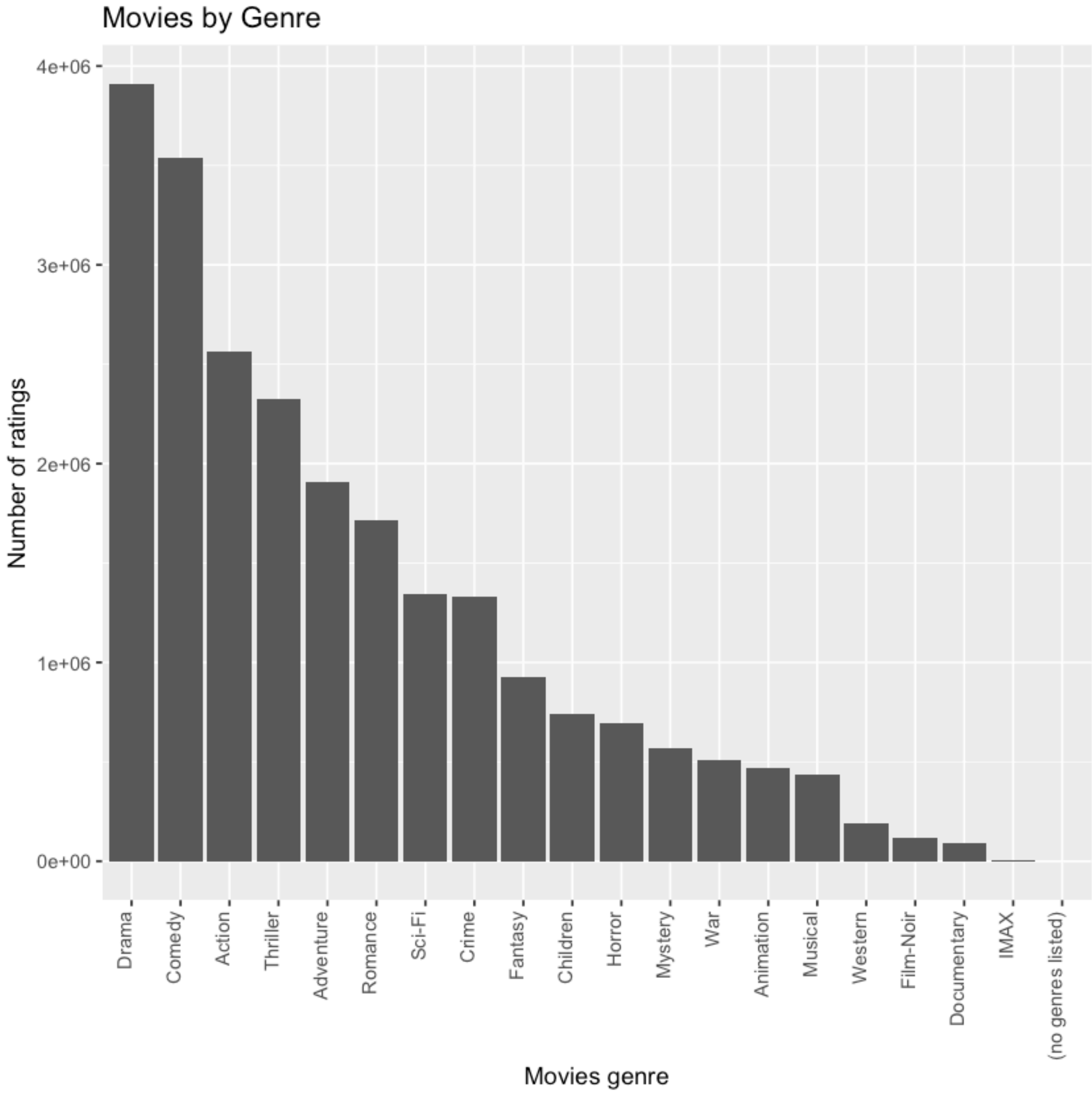
Not surprisingly, the top 3 rated genres are **Drama**, **Comedy**, and **Action**.

In [31]:
```
movies_genre %>% filter(genres == "(no genres listed)")
```

userId	movieId	rating	timestamp	title	genres
7701	8606	5.0	1190806786	Pull My Daisy (1958)	(no genres listed)
10680	8606	4.5	1171170472	Pull My Daisy (1958)	(no genres listed)
29097	8606	2.0	1089648625	Pull My Daisy (1958)	(no genres listed)
46142	8606	3.5	1226518191	Pull My Daisy (1958)	(no genres listed)
57696	8606	4.5	1230588636	Pull My Daisy (1958)	(no genres listed)
64411	8606	3.5	1096732843	Pull My Daisy (1958)	(no genres listed)
67385	8606	2.5	1188277325	Pull My Daisy (1958)	(no genres listed)

Note: The movie **Pull My Daisy (1958)** (which is rated by 7 users) has no genre listed.

In [32]:
```
ggplot(data = genres_ratings, aes(x = reorder(genres, -count), y = 
count)) +
        geom_bar(stat = "identity") +
        theme(axis.text.x = element_text(angle = 90, hjust = 1, vju
st = 0)) +
        labs(title = "Movies by Genre", x = "Movies genre", y = "Nu
mber of ratings")
```



In [33]:

```
# What are the most popular genres?

# Best genres (by ratings average)
top_genres <- movies_genre %>%
  group_by(genres) %>%
  summarise(count = n(), avg = mean(rating)) %>%
  arrange(desc(avg))

top_genres
```

genres	count	avg
Film-Noir	118541	4.011625
Documentary	93066	3.783487
War	511147	3.780813
IMAX	8181	3.767693
Mystery	568332	3.677001
Drama	3910127	3.673131
Crime	1327715	3.665925
(no genres listed)	7	3.642857
Animation	467168	3.600644
Musical	433080	3.563305
Western	189394	3.555918
Romance	1712100	3.553813
Thriller	2325899	3.507676
Fantasy	925637	3.501946
Adventure	1908892	3.493544
Comedy	3540930	3.436908
Action	2560545	3.421405
Children	737994	3.418715
Sci-Fi	1341183	3.395743
Horror	691485	3.269815

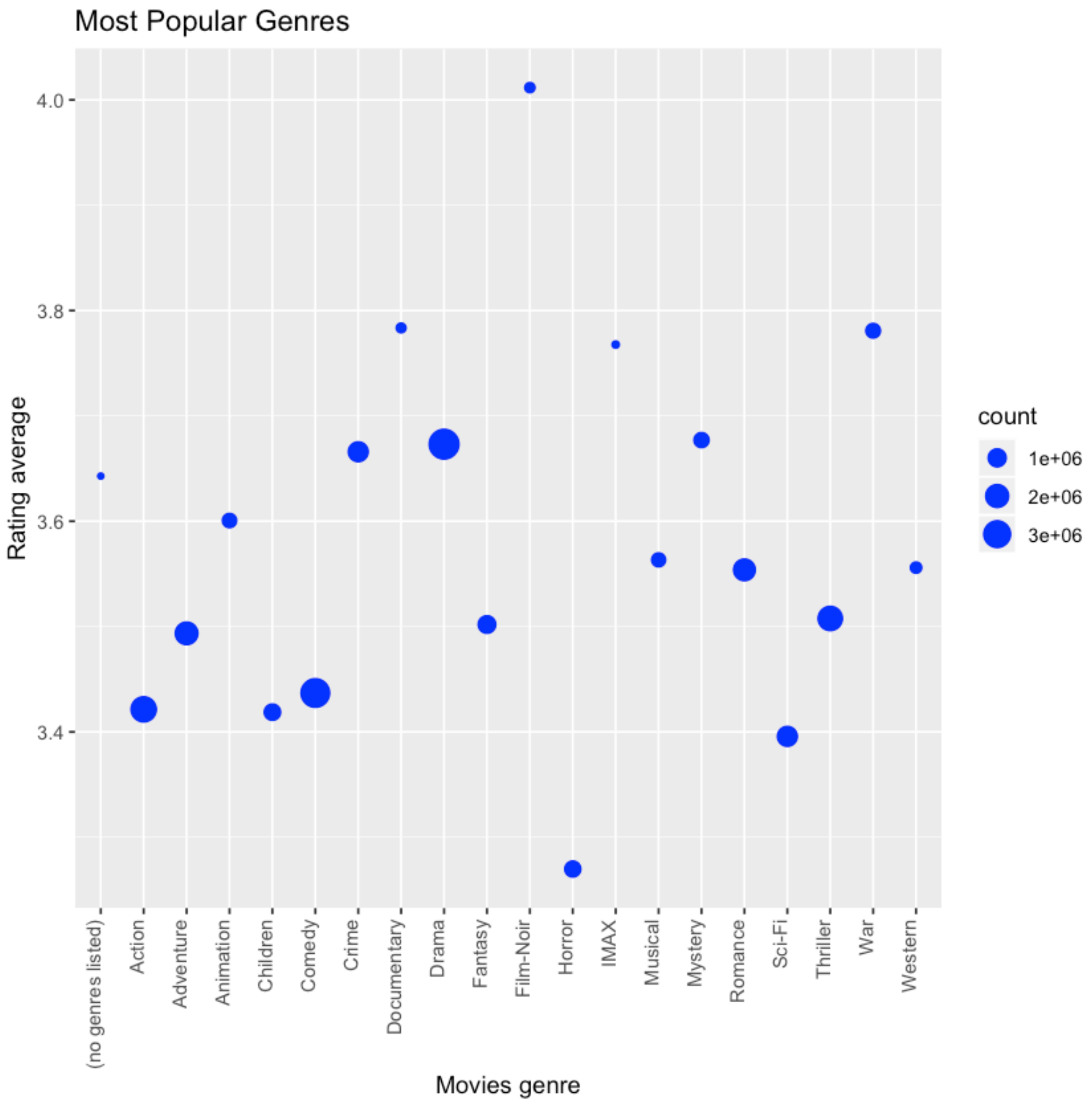
The top 3 most liked genres are **Film-Noir**, **Documentary**, and **War**. However, these genres are not often reviewed, so the ranking is not representative of the popularity of the genre. We can use a weighted average to take this bias into account.

In [34]:
```
# R = average of the movie ratings
# v = number of ratings for the movie
# m = minimum ratings required to be listed in the Top movies
# C = the mean rating across the whole dataset

wr <- function(R, v, m, C) {
  return (v/(v+m))*R + (m/(v+m))*C
}

new_top_genres <- movies_genre %>%
    group_by(genres) %>%
    summarise(count = n(), avg = mean(rating)) %>%
    mutate(weighted_rating = wr(avg, count, 1000, mean(avg))) %>%
    arrange(desc(weighted_rating))

new_top_genres
```

genres	count	avg	weighted_rating
Drama	3910127	3.673131	0.999744319
Comedy	3540930	3.436908	0.999717668
Action	2560545	3.421405	0.999609611
Thriller	2325899	3.507676	0.999570243
Adventure	1908892	3.493544	0.999476410
Romance	1712100	3.553813	0.999416263
Sci-Fi	1341183	3.395743	0.999254945
Crime	1327715	3.665925	0.999247393
Fantasy	925637	3.501946	0.998920829
Children	737994	3.418715	0.998646809
Horror	691485	3.269815	0.998555925
Mystery	568332	3.677001	0.998243556
War	511147	3.780813	0.998047436
Animation	467168	3.600644	0.997864015
Musical	433080	3.563305	0.997696277
Western	189394	3.555918	0.994747734
Film-Noir	118541	4.011625	0.991634669
Documentary	93066	3.783487	0.989369166
IMAX	8181	3.767693	0.891079403
(no genres listed)	7	3.642857	0.006951341

So, the 3 most popular genres, when considering the count of reviews as well, are confirmed to be **Drama**, **Comedy**, and **Action**.

In [35]:
```
# Most popular genres
ggplot(data = new_top_genres, aes(x = genres, y = avg)) +
    geom_point(aes(size = count),color = "blue") +
    theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust=0
)) +
    labs(title = "Most Popular Genres", x = "Movies genre", y = "Ra
ting average")
```



We note that the top 4 most highly rated genres are not very popular. One reason would be that users who rate these genres are rather the aficionados.

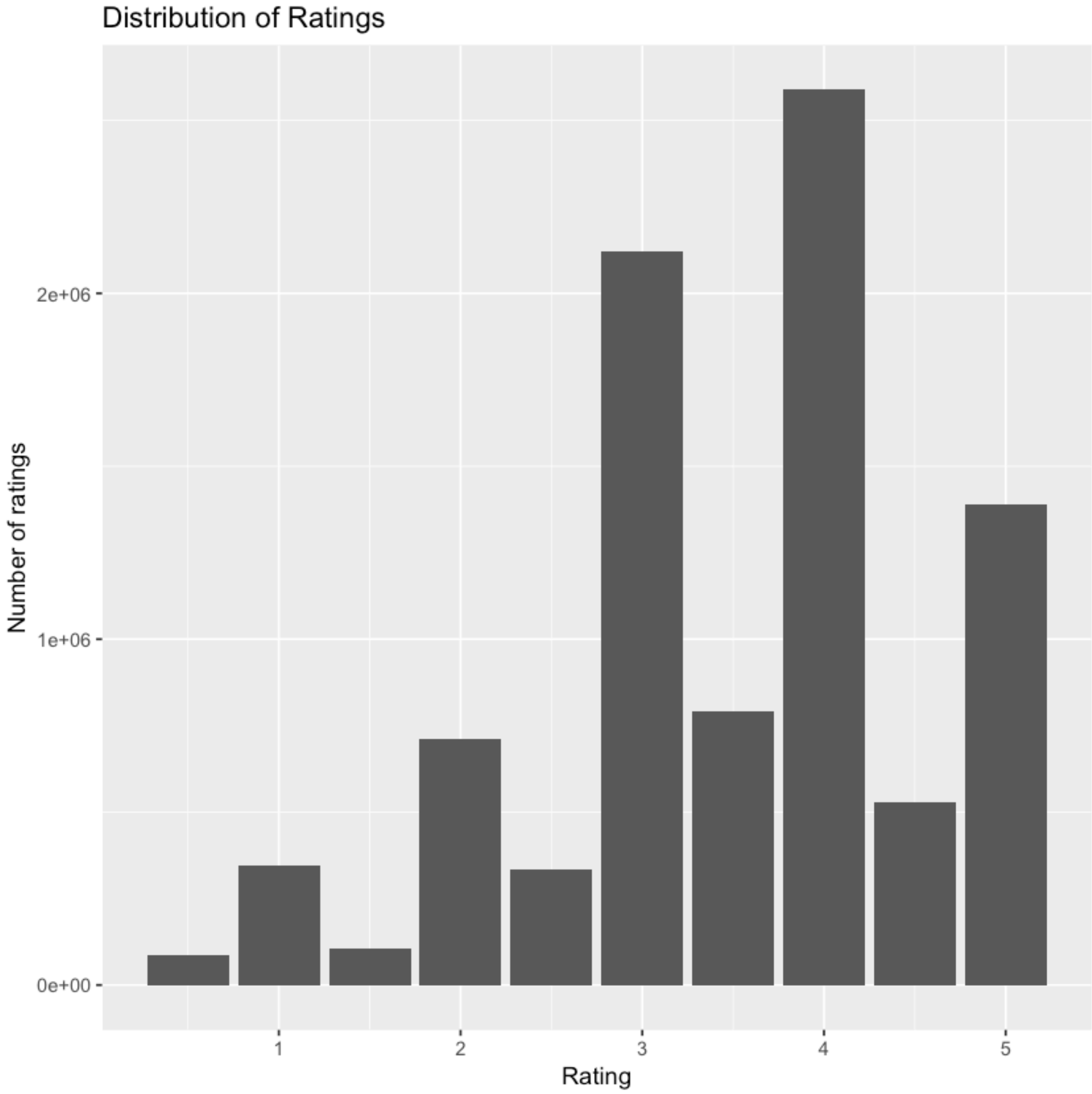
In [36]:
```
# Clean up memory
rm(edx_movies, movies_year, movies_votes, top_movies, wr, new_top_m
ovies, top10_movies,
   title_year, movies_title_year,
   movies_genre, genres_ratings, top_genres, new_top_genres)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11618820	620.6	48539288	2592.3	37024444	1977.4
Vcells	91342821	696.9	385640714	2942.3	518721523	3957.6

In [37]:
```
# --- EXPLORING RATINGS -------------------------------------

summary(edx$rating)
```

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

In [38]:
```
# Distribution of ratings
ggplot(data = edx, aes(x = rating)) +
    geom_bar() +
    labs(title = "Distribution of Ratings", x = "Rating", y = "Numb
er of ratings")
```



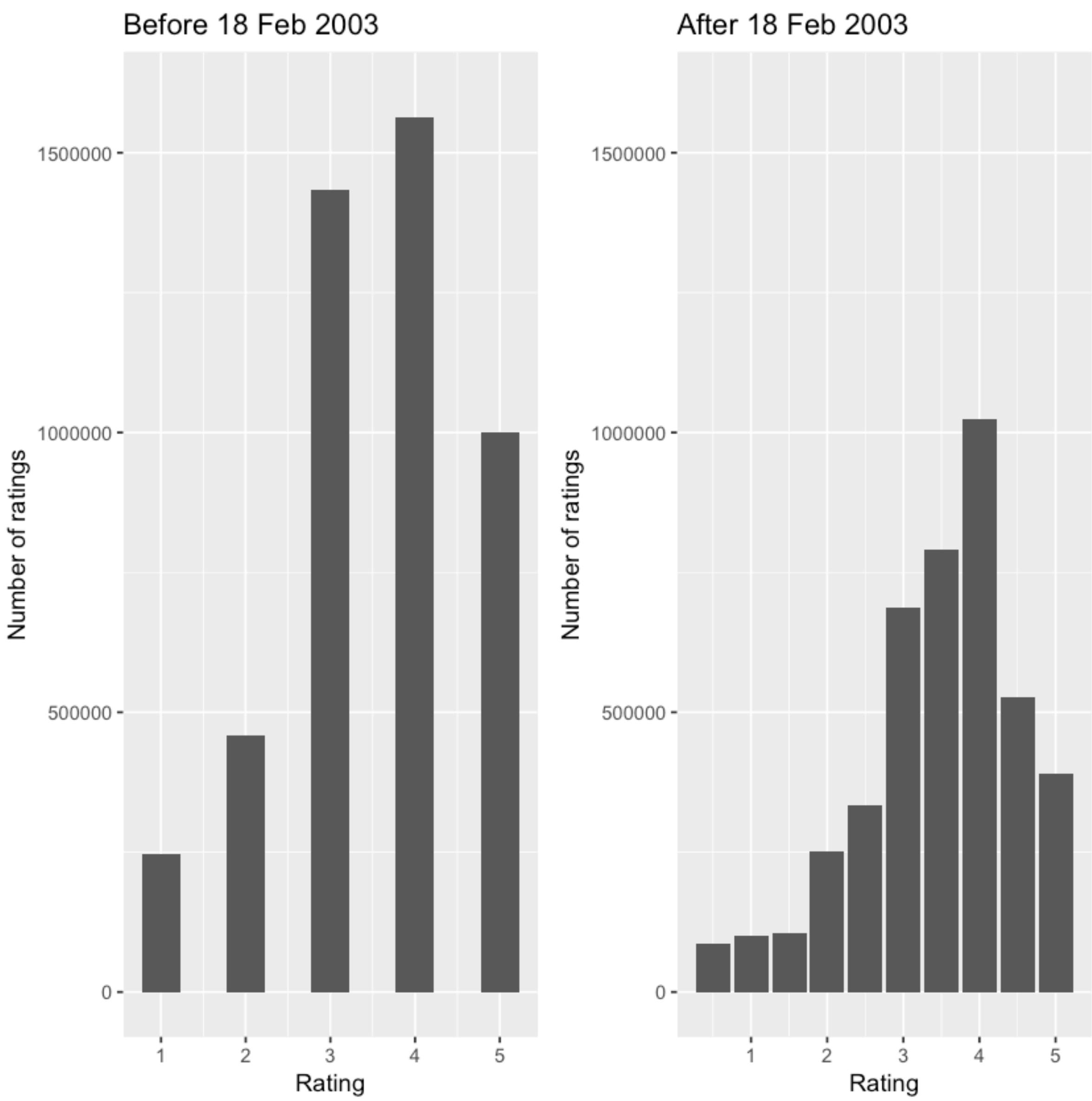
In [39]:
```
# How do the ratings distributions compare before and after half-st
ar scores are allowed?
# The half-star rating has been implemented from 18 February 2003 (
timestamp = 1045526400

edx_before <- subset(edx, timestamp < 1045526400)
edx_after <- subset(edx, timestamp >= 1045526400)
```

In [40]:
```
# Numbers of rows before and after 18 Feb 2003
cat("There are", nrow(edx_before), "ratings before 18 Feb 2003, wit
hout half-star scoring and", nrow(edx_after), "ratings after 18 Feb
2003, with half-star scoring.")
```

```
There are 4702794 ratings before 18 Feb 2003, without half-star sc
oring and 4297261 ratings after 18 Feb 2003, with half-star scorin
g.
```

In [41]:

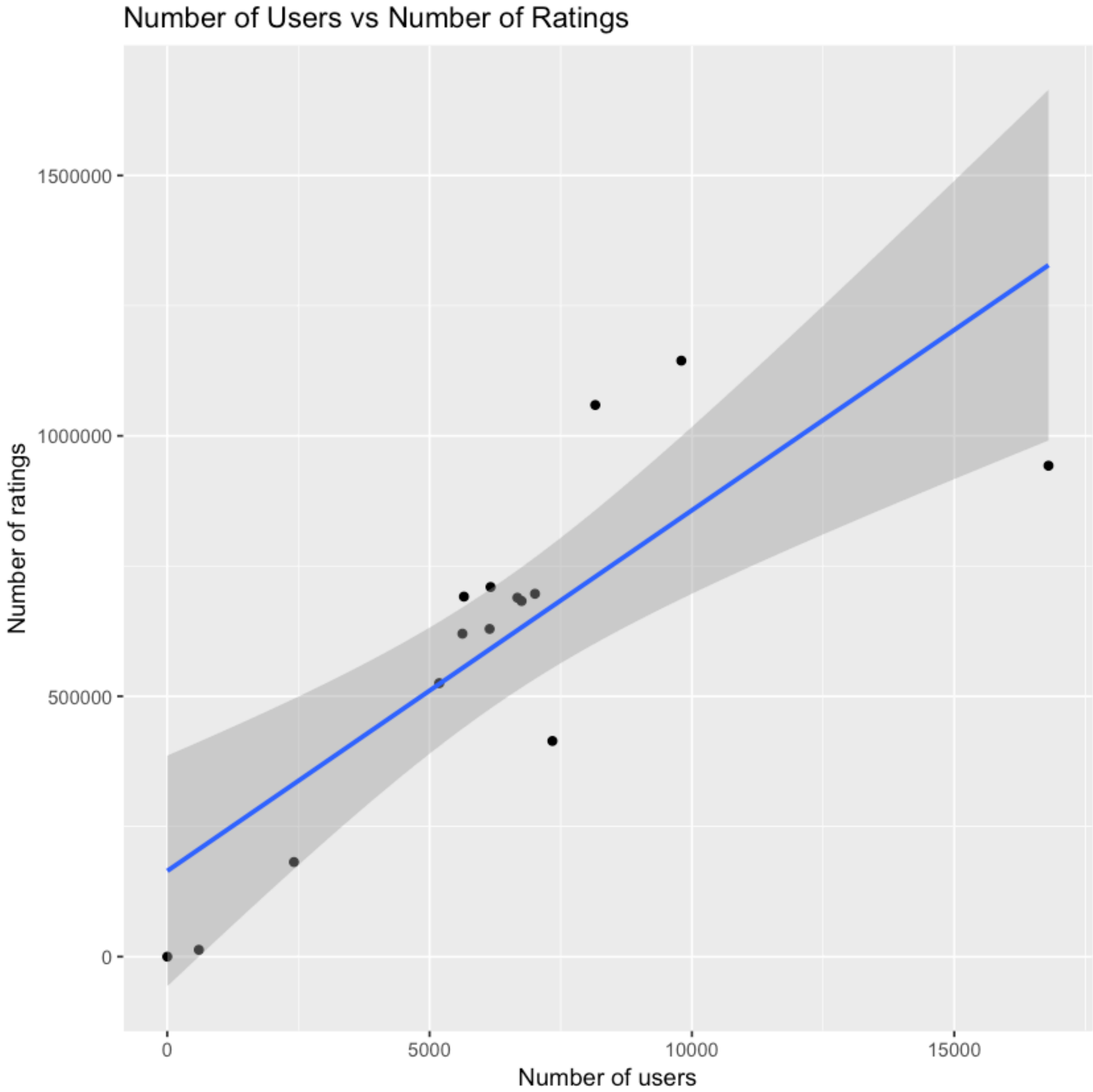
```
# Distribution of ratings before 2003-02-18 (timestamp = 1045526400
)
pbef <- ggplot(data=edx_before, aes(x = rating)) +
    geom_bar() +
    ylim(0, 1600000) +
    labs(title = "Before 18 Feb 2003", x = "Rating", y = "Number of
ratings")

# Distribution of ratings after 2003-02-18 (timestamp = 1045526400)
paft <- ggplot(data = edx_after, aes(x = rating)) +
    geom_bar() +
    ylim(0, 1600000) +
    labs(title = "After 18 Feb 2003", x = "Rating", y = "Number of
ratings")

grid.arrange(pbef, paft, ncol = 2)
```



In [42]:
```
# Ratings per year
edx_year_rating <- edx %>% transform(timestamp = format(as.POSIXlt(
timestamp, origin = "1970-01-01"), "%Y"))

# Number of distinct users per year
users_year <- edx_year_rating %>%
    select(timestamp, userId) %>%
    group_by(timestamp) %>%
    summarise(count_users = n_distinct(userId)) %>%
    arrange(timestamp)

# Number of ratings per year
ratings_year <- edx_year_rating %>%
    select(timestamp, rating) %>%
    group_by(timestamp) %>%
    summarise(count_ratings = n()) %>%
    arrange(timestamp)

rates <- users_year %>%
    left_join(ratings_year) %>%
    mutate(rate = count_ratings / count_users)
```

```
Joining, by = "timestamp"
```

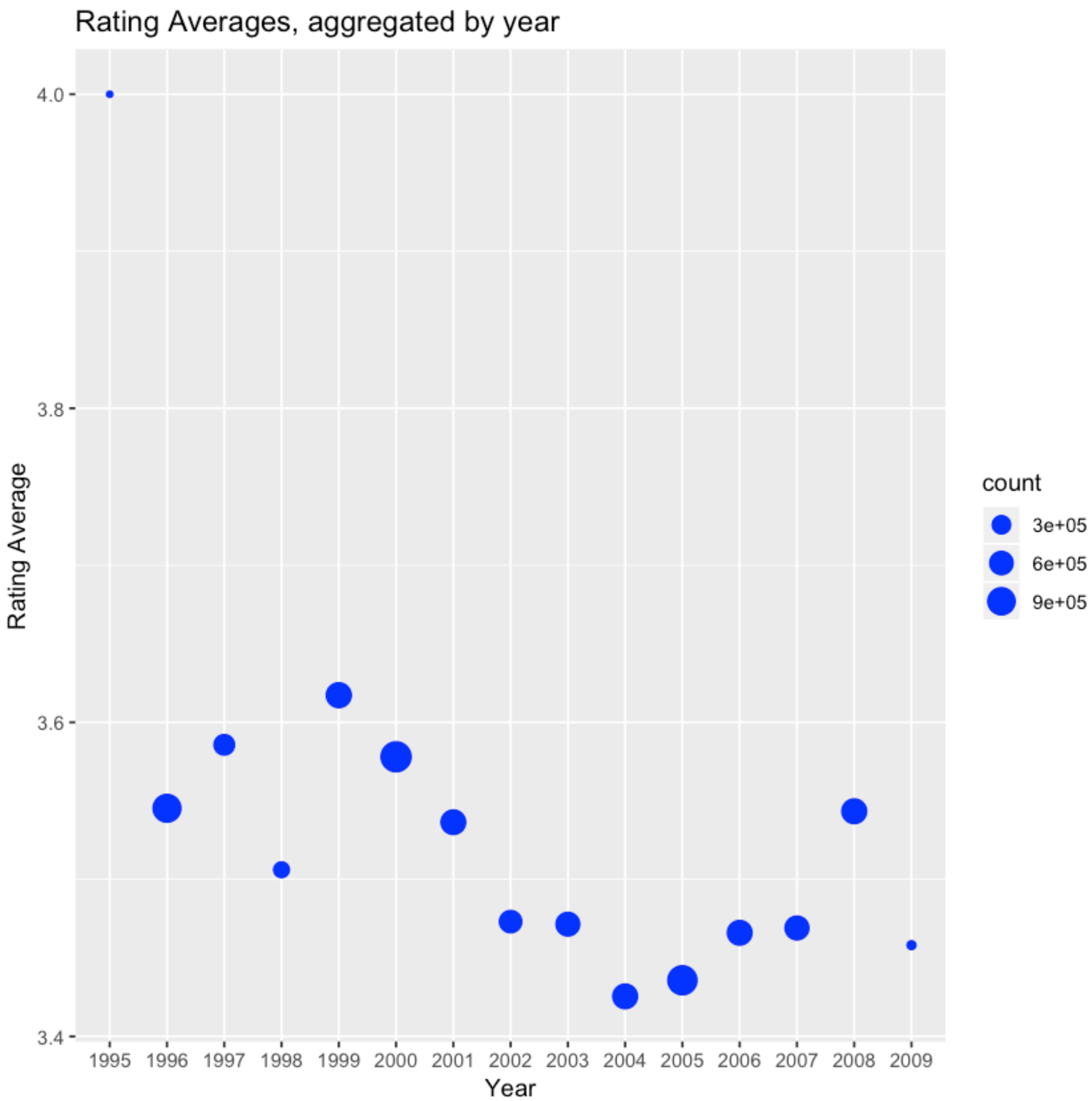
In [43]:
```
ggplot(data = rates, aes(x = count_users, y = count_ratings)) +
                geom_point() +
                geom_smooth(method = "lm") +
                labs(title = "Number of Users vs Number of Ratings"
, x = "Number of users", y = "Number of ratings")
```



Not surprisingly, the number of users is correlated with the number of ratings.

In [44]:

```
# Ratings average per year

avg_rating_year <- edx_year_rating %>%
  group_by(timestamp) %>%
  summarise(count = n(), average = mean(rating), std = sd(rating),
median = median(rating), min = min(rating), max = max(rating)) %>%
  arrange(desc(average))

ggplot(data = avg_rating_year, aes(x = timestamp, y = average)) +
              geom_point(aes(size = count),color = "blue") +
              labs(title = "Rating Averages, aggregated by year",
x = "Year", y = "Rating Average")
```



As seen earlier, rating averages are rather consistent, between 3.4 and 3.6 stars. The average in 1995, with only one rating, can be considered as an outlier.

In [45]:
```
# Clean up memory
rm(edx_before, edx_after, pbef, paft,
   edx_year_rating, users_year, ratings_year, rates, avg_rating_yea
r)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11640098	621.7	38831430	2073.9	37024444	1977.4
Vcells	91378395	697.2	308512571	2353.8	518721523	3957.6

Predictive Model

In [46]:
```
# --- USED LIBRARIES ---------------------------------------

if(!require(knitr)) install.packages("knitr", repos = "http://cran.
us.r-project.org")
# if(!require(e1071)) install.packages("e1071", repos = "http://cra
n.r-project.org")
```

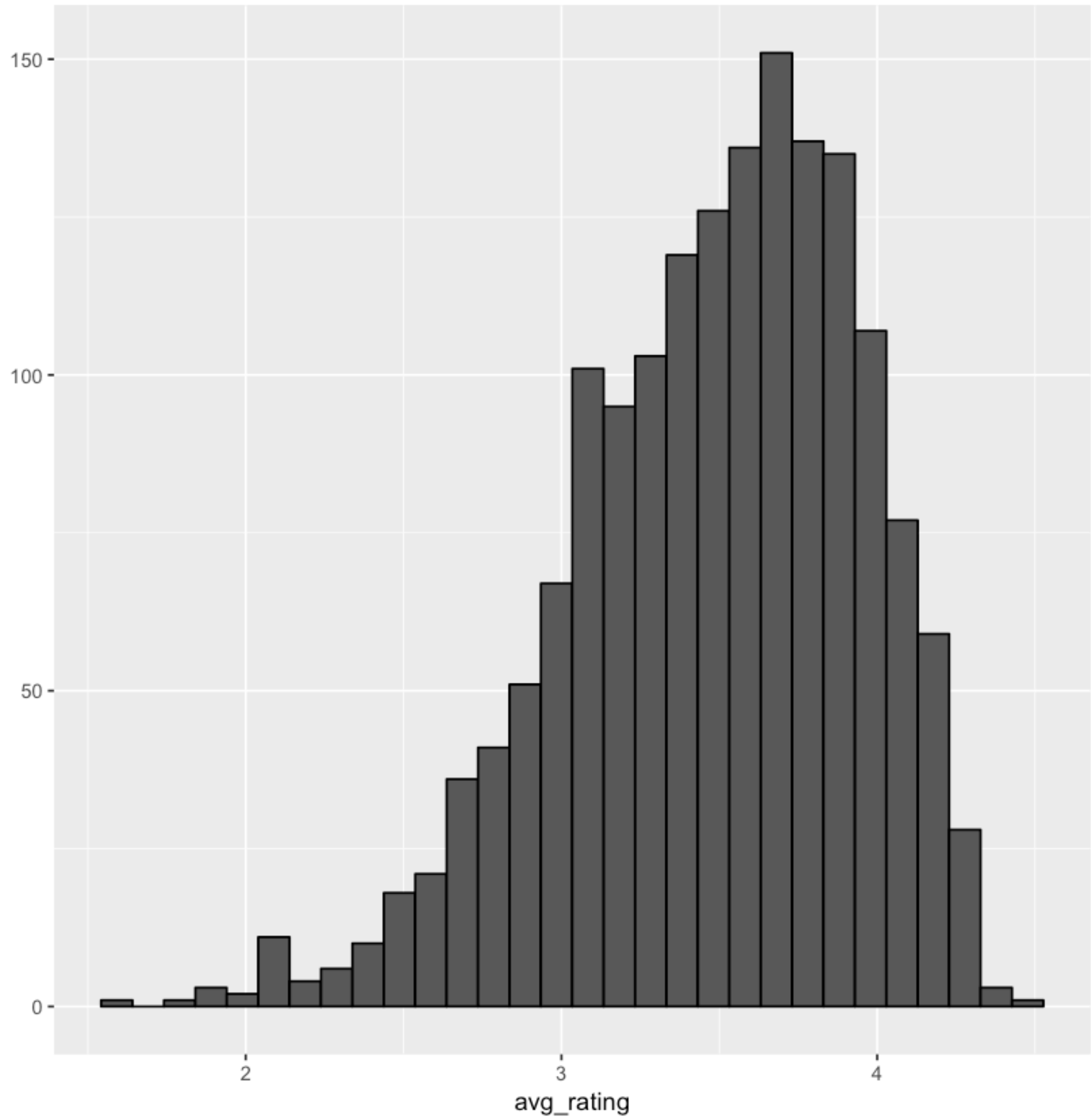
```
Loading required package: knitr
```

In [47]:
```
# --- SPLIT TRAIN/TEST SETS --------------------------------

set.seed(699)
test_index <- createDataPartition(y = edx$rating, times = 1, p = 0.
2, list = FALSE)
train_set <- edx[-test_index,]
test_set <- edx[test_index,]

# Use semi_join() to ensure that all users and movies in the test s
et are also in the training set
test_set <- test_set %>%
  semi_join(train_set, by = "movieId") %>%
  semi_join(train_set, by = "userId")
```

In [48]:

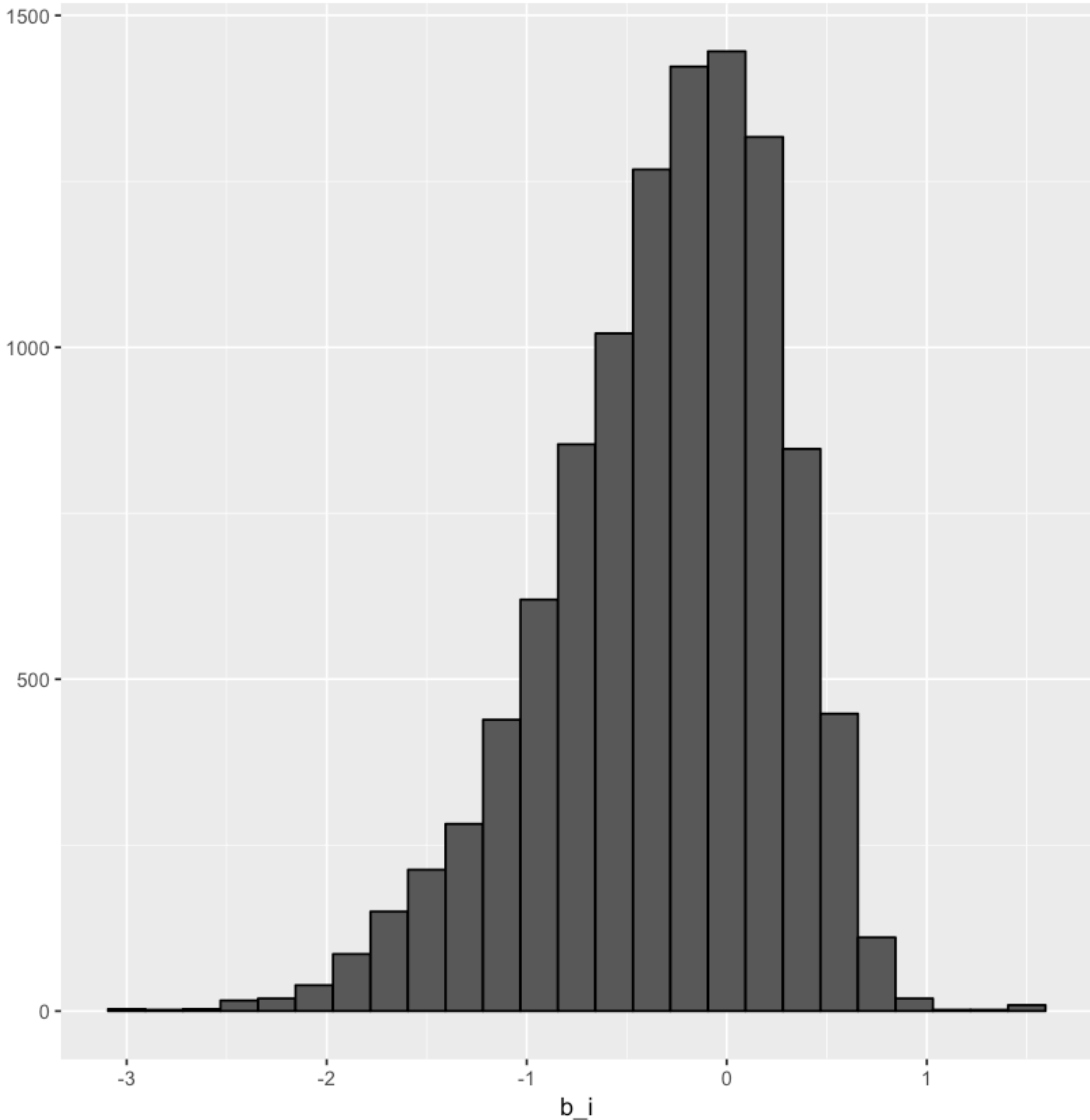
```
# --- MODELING WITH JUST THE AVERAGE -----------------------

# RMSE as loss function, which computes the errors between ratings
and predicted ratings.
RMSE <- function(true_ratings, predicted_ratings){
  sqrt(mean((true_ratings - predicted_ratings)^2))
}

# The estimate here that minimizes the RMSE is just the average rat
ing of all movies across all users.
# We compute this average on the training data...
mu <- mean(train_set$rating)
cat("The average rating of all movies across all users is:", mu)

# Let's plot the average rating for movies that are rated at least
1000 times.
train_set %>% group_by(movieId) %>%
  filter(n()>=1000) %>%
  summarize(avg_rating = mean(rating)) %>%
  qplot(avg_rating, geom = "histogram", color = I("black"), bins=30
, data = .)

# ...and we predict all unknown ratings with this average.
predictions <- rep(mu, nrow(test_set))

# Then we compute the RMSE.
naive_rmse <- RMSE(test_set$rating, predictions)
cat("The RMSE with just the average method is:", naive_rmse)
```

```
The average rating of all movies across all users is: 3.512453
The RMSE with just the average method is: 1.060247
```



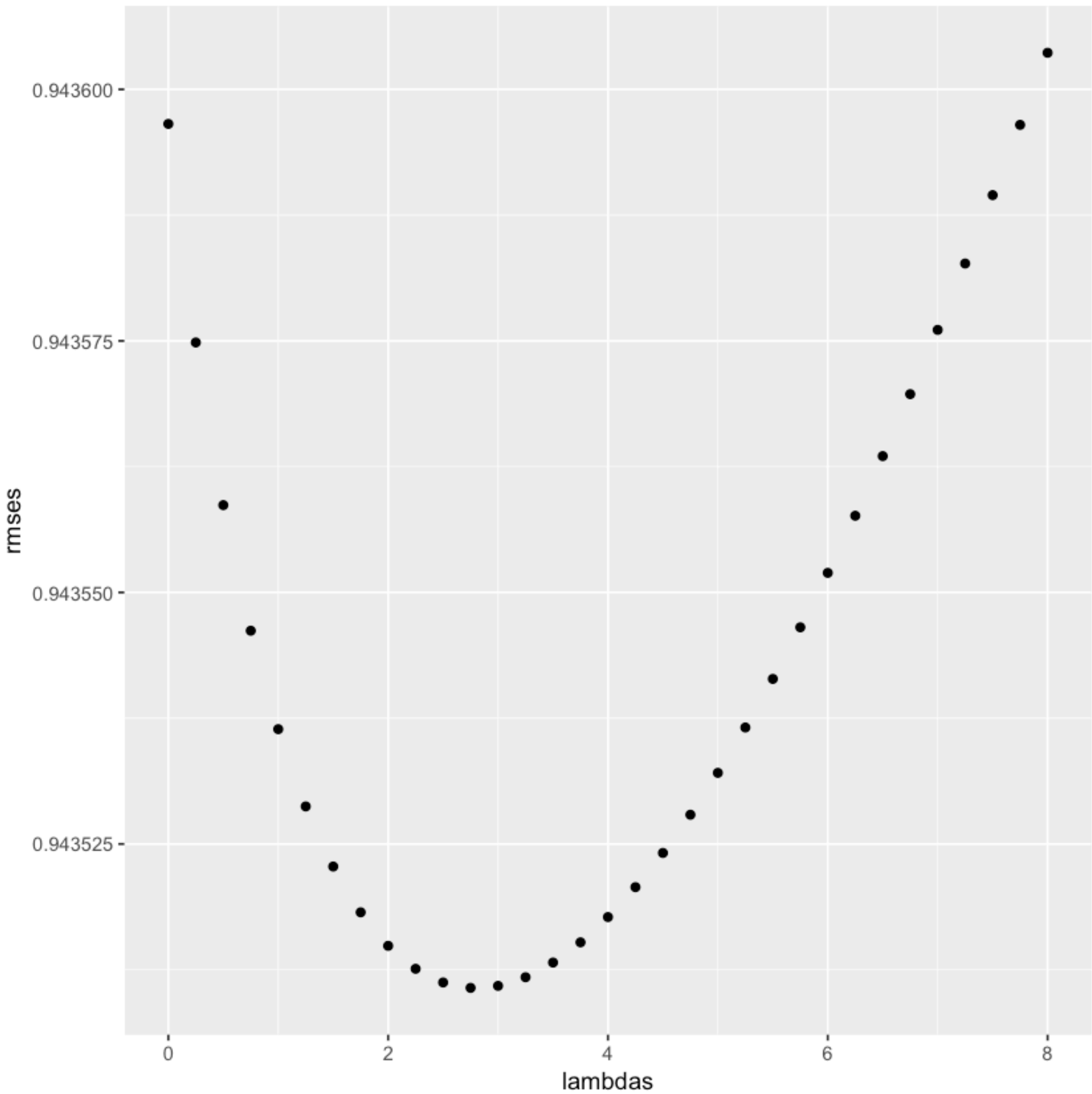
In [49]:
```
# --- MODELING MOVIE EFFECT --------------------------------

# Create a table that's going to store the results that we obtain a
s we're goinng to compare different effects.
rmse_results <- data_frame(method = "Just the average", RMSE = naiv
e_rmse)

movie_means <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu))

qplot(b_i, geom = "histogram", color = I("black"), bins=25, data =
movie_means)

joined <- test_set %>%
  left_join(movie_means, by='movieId')

# Note that as we ensured above that all users and movies in the te
st set are also in the training set,
# we don't need to handle NAs with the left_join()

predicted_ratings <- mu + joined$b_i

model1_rmse <- RMSE(predicted_ratings, test_set$rating)

rmse_results <- bind_rows(rmse_results,
                          data_frame(method = "Movie effect model",
                                     RMSE = model1_rmse ))
rmse_results %>% kable
```

method	RMSE
Just the average	1.0602472
Movie effect model	0.9435966



In [50]:
```
# --- REGULARIZATION OF THE MOVIE EFFECT --------------------

# The largest movie effects are with movies that have few ratings.
# So, we use regularization to penalize large estimates that come f
rom small sample sizes.

# Compute regularized estimates of b_i using lambda (penalty term).
Let's first try a few values of lambda and pick the best one.
lambdas <- seq(0, 8, 0.25)

tmp <- train_set %>%
  group_by(movieId) %>%
  summarize(sum = sum(rating - mu), n_i = n())

rmses <- sapply(lambdas, function(l){
  joined <- test_set %>%
    left_join(tmp, by='movieId') %>%
    mutate(b_i = sum/(n_i+l))
    predicted_ratings <- mu + joined$b_i
    return(RMSE(predicted_ratings, test_set$rating))
})

cat("The best lambda (which minimizes the RMSE) for the movie effec
t is:", lambdas[which.min(rmses)])

qplot(lambdas, rmses)
```

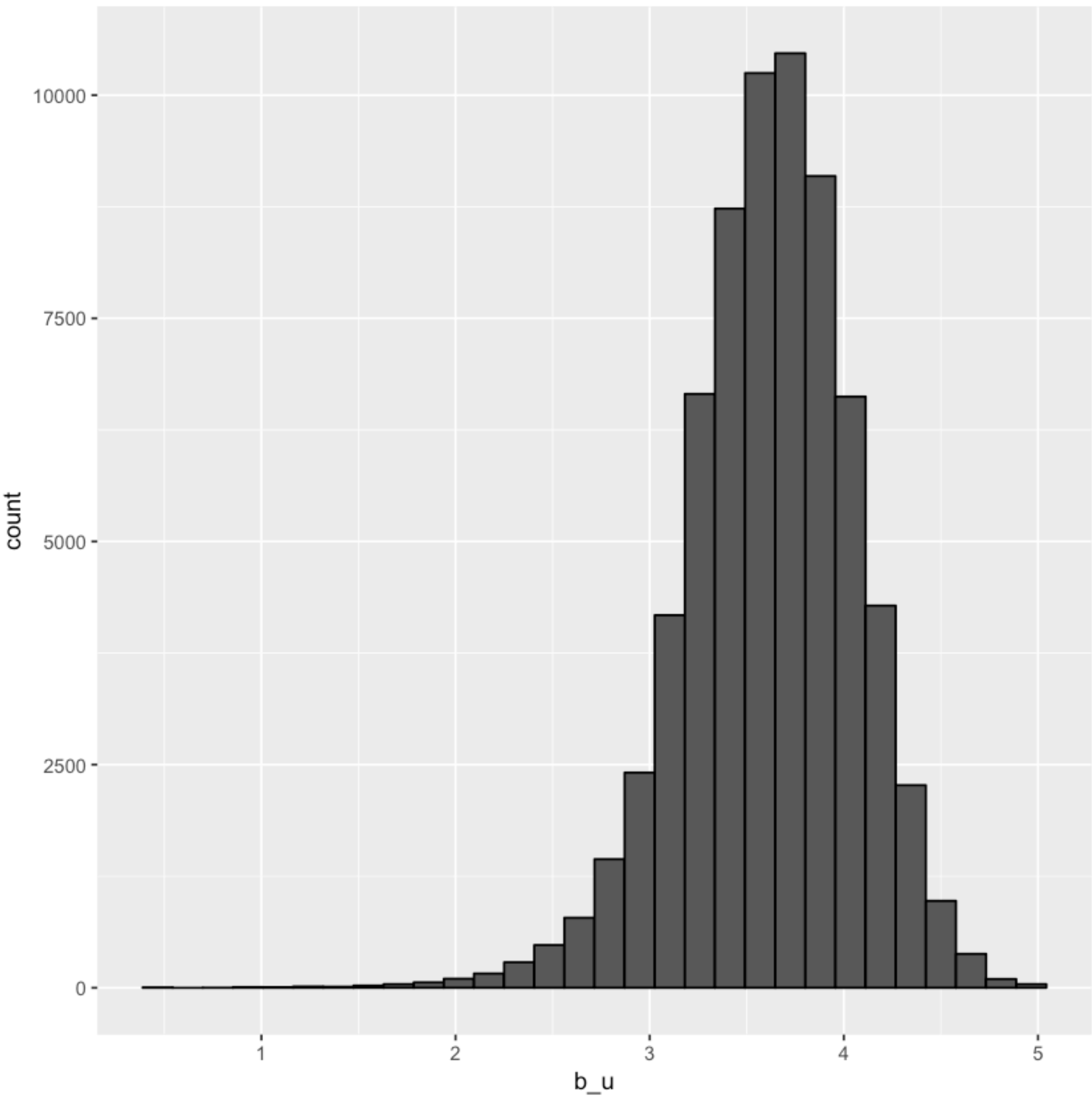
```
The best lambda (which minimizes the RMSE) for the movie effect is
: 2.75
```



In [51]:
```
# So it looks like a value of lambda = 2.75 gives us the smallest R
MSE

lambda <- 2.75

movie_reg_means <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mu)/(n()+lambda), n_i = n())

joined <- test_set %>%
  left_join(movie_reg_means, by='movieId') %>%
  replace_na(list(b_i=0))

predicted_ratings <- mu + joined$b_i

model1_reg_rmse <- RMSE(predicted_ratings, test_set$rating)

rmse_results <- bind_rows(rmse_results,
                          data_frame(method = "Regularized movie ef
fect model, lambda = 2.75",
                                     RMSE = model1_reg_rmse ))
rmse_results %>% kable
```

```
|method                                      |      RMSE|
|:-------------------------------------------|---------:|
|Just the average                            | 1.0602472|
|Movie effect model                          | 0.9435966|
|Regularized movie effect model, lambda = 2.75 | 0.9435107|
```

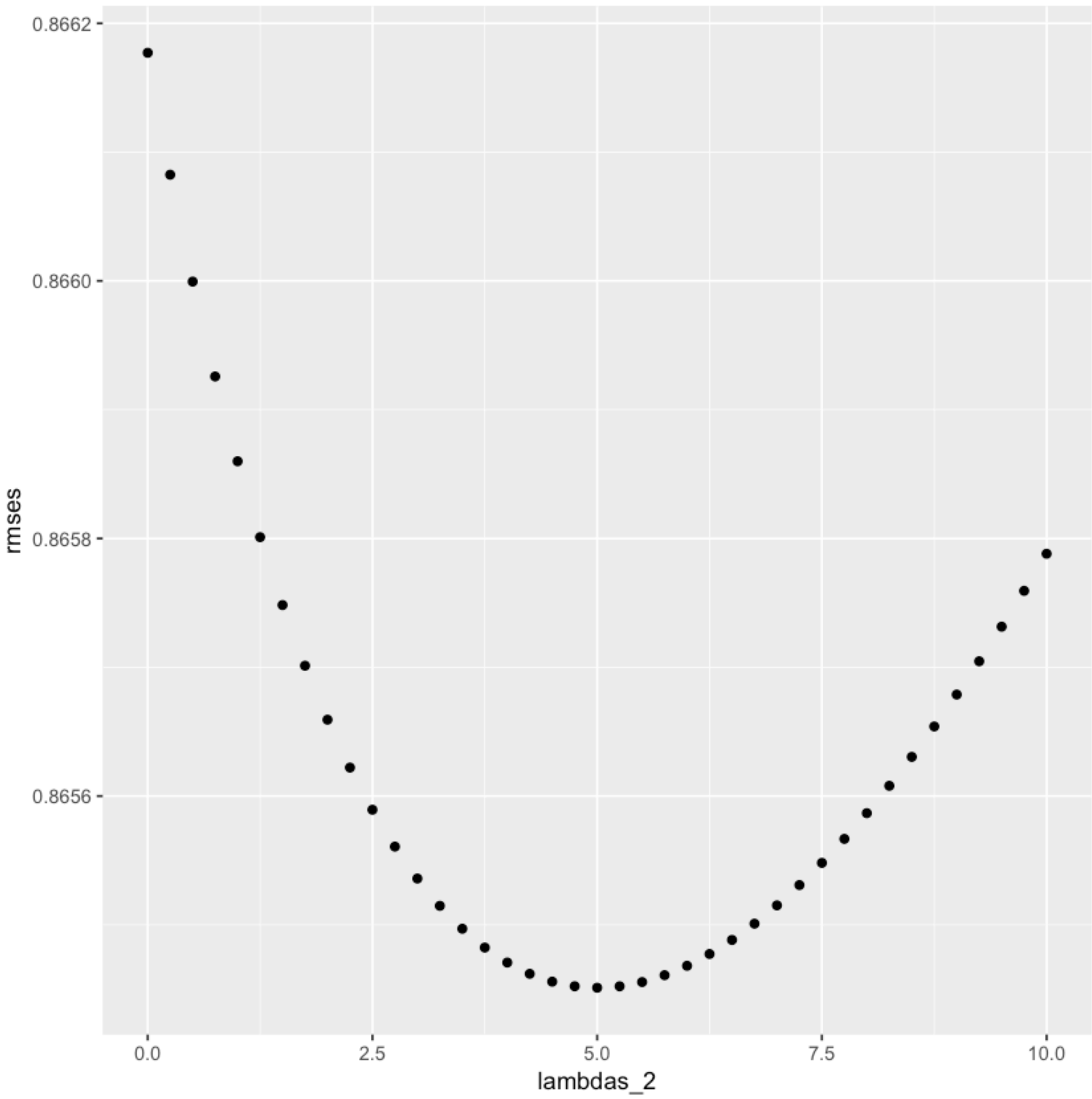
In [53]:
```
# --- MODELING USER AND MOVIE EFFECTS -----------------------------
-----

# Let's plot the average rating for users who have rated at least 1
00 movies
train_set %>%
  group_by(userId) %>%
  summarize(b_u = mean(rating)) %>%
  filter(n() >= 100) %>%
  ggplot(aes(b_u)) +
  geom_histogram(bins = 30, color  = "black")
```



count
10000
7500
5000
2500
0
1
2
3
4
5
b_u

In [54]:
```
# As with the movies, the largest user effect are for those that ra
te few movies.
# We again use regularization, this time with a different lambda (l
ambda_2). Let's first try a few values of lambda_2 and pick the bes
t one.
# Note: This process could take several minutes

lambdas_2 <- seq(0, 10, 0.25)

rmses <- sapply(lambdas_2, function(l){

  mu <- mean(train_set$rating)

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

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

  predicted_ratings <- test_set %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    mutate(pred = mu + b_i + b_u) %>%
    .$pred

    return(RMSE(predicted_ratings, test_set$rating))
})

cat("The best lambda_2 (which minimizes the RMSE) for the user and
movie effects is", lambdas_2[which.min(rmses)])

qplot(lambdas_2, rmses)
```

```
The best lambda_2 (which minimizes the RMSE) for the user and movi
e effects is 5
```



In [55]:
```
# So it looks like a value of lambda_2 = 5 gives us the smallest RM
SE

lambda_2 <- 5

user_reg_means <- train_set %>%
  left_join(movie_reg_means) %>%
  mutate(resids = rating - mu - b_i) %>%
  group_by(userId) %>%
  summarize(b_u = sum(resids)/(n()+lambda_2))

joined <- test_set %>%
  left_join(movie_reg_means, by='movieId') %>%
  left_join(user_reg_means, by='userId') %>%
  replace_na(list(b_i=0, b_u=0))

predicted_ratings <- mu + joined$b_i + joined$b_u

model2_reg_rmse <- RMSE(predicted_ratings, test_set$rating)

rmse_results <- bind_rows(rmse_results,
                          data_frame(method = "Regularized movie an
d user effects model, lambda2 = 5",
                                     RMSE = model2_reg_rmse ))
rmse_results %>% kable
```

```
Joining, by = "movieId"


|method                                              |      RMSE
|
|:---------------------------------------------------|---------:
|
|Just the average                                    | 1.0602472
|
|Movie effect model                                  | 0.9435966
|
|Regularized movie effect model, lambda = 2.75       | 0.9435107
|
|Regularized movie and user effects model, lambda2 = 5 | 0.8654773
|
```

In [56]:
```
# --- MATRIX DECOMPOSITION ---------------------------------------
-----

# We use PCA to uncover patterns in user/movie relationships

# First, tet's remove the user and movie bias to create residuals
new_train_set <- train_set %>%
  left_join(movie_reg_means, by = "movieId") %>%
  left_join(user_reg_means, by = "userId") %>%
  mutate(resids = rating - mu - b_i - b_u)
```

In [57]:
```
# Next we create a matrix using spread()
# Note: This process could take several minutes

r <- new_train_set %>%
  select(userId, movieId, resids) %>%
  spread(movieId, resids) %>%
  as.matrix()

rownames(r) <- r[,1]
r <- r[,-1]
r[is.na(r)] <- 0 # For the sake of simplicity, we just apply 0 to a
ll missing data
```

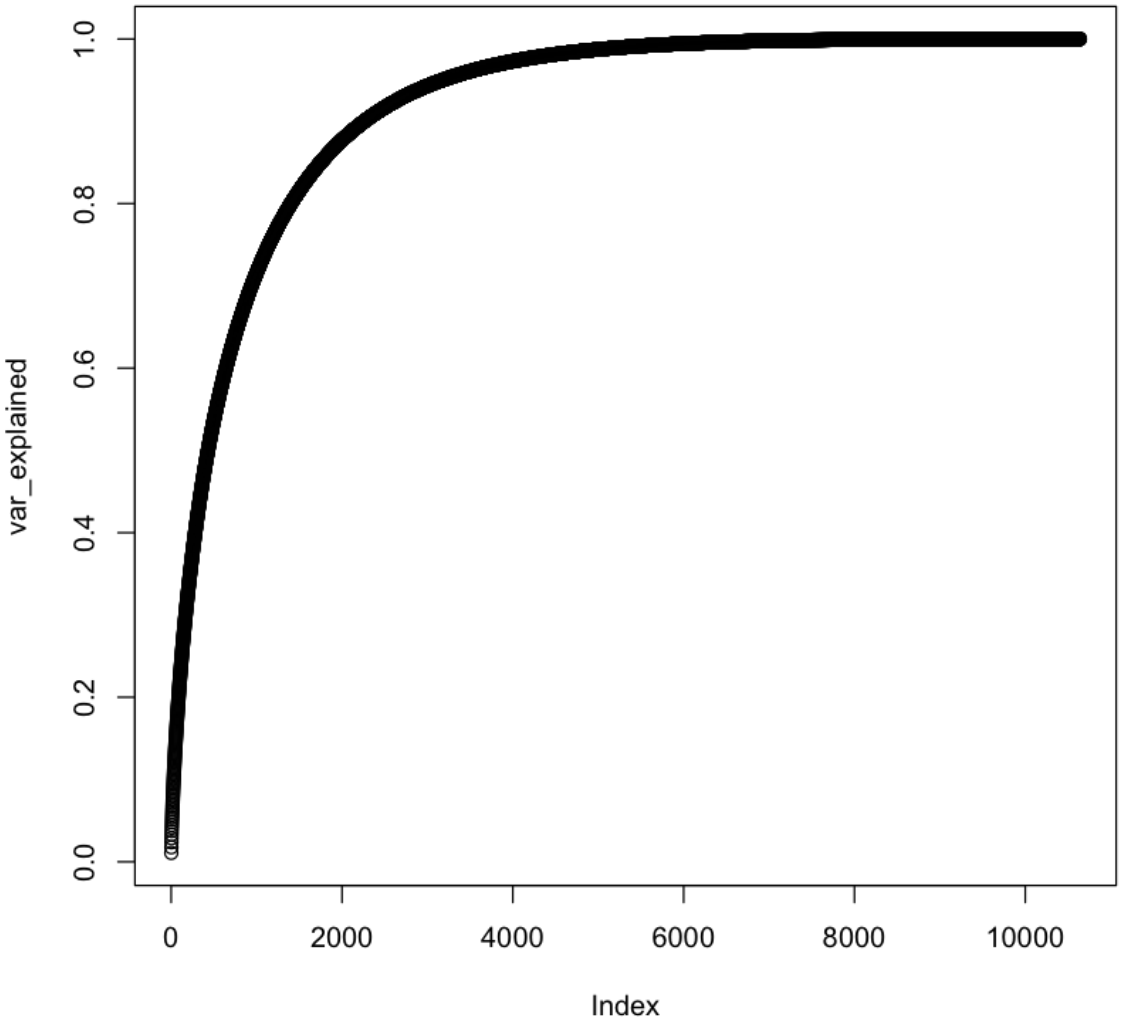
In [58]:
```
# Singular value decomposition
# Note: This process could take several long minutes

pca <- prcomp(r - rowMeans(r), center = TRUE, scale = FALSE)
```

In [59]:
```
dim(pca$x) # Principal components
dim(pca$rotation) # Users' effects
```

69878 10639

10639 10639

In [60]:
```
# Variability
var_explained <- cumsum(pca$sdev^2/sum(pca$sdev^2))
plot(var_explained)
```



In [61]:
```
# Factorization of the 4000 first principal components, which expla
in almost all the variability

k <- 4000

pred <- pca$x[,1:k] %*% t(pca$rotation[,1:k])
colnames(pred) <- colnames(r)
```

In [62]:
```
# Note: This process could take several very long minutes

interaction <-
    data.frame(userId = as.numeric(rownames(r)), pred, check.names
= FALSE) %>%
    tbl_df %>%
    gather(movieId, b_ui, -userId) %>%
    mutate(movieId = as.numeric(movieId))
```

In [63]:

```
# Clean up memory
rm(pred, pca, r)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11688902	624.3	38831430	2073.9	38831430	2073.9
Vcells	2453317016	18717.4	7543008298	57548.6	6284171678	47944.5

In [64]:

```
# Note: This process could take several very long hours

joined <- test_set %>%
  left_join(movie_reg_means, by='movieId') %>%
  left_join(user_reg_means, by='userId') %>%
  left_join(interaction, by=c('movieId','userId')) %>%
  replace_na(list(b_i=0, b_u=0, b_ui=0))

predictions <- joined %>% mutate(resids = rating - mu - joined$b_i
- joined$b_u - joined$b_ui)
head(predictions)
```

userId	movieId	rating	timestamp	title	genres	b_i
1	370	5	838984596	Naked Gun 33 1/3: The Final Insult (1994)	Action|Comedy	-0.5
1	520	5	838984679	Robin Hood: Men in Tights (1993)	Comedy	-0.5
2	590	5	868245608	Dances with Wolves (1990)	Adventure|Drama|Western	0.23
2	648	2	868244699	Mission: Impossible (1996)	Action|Adventure|Mystery|Thriller	-0.1
2	719	3	868246191	Multiplicity (1996)	Comedy	-0.5
2	786	3	868244562	Eraser (1996)	Action|Drama|Thriller	-0.3

In [65]:
```
predicted_ratings <- mu + predictions$b_i + predictions$b_u + predi
ctions$b_ui

matrix_decomp_model_rmse <- RMSE(predicted_ratings, predictions$rat
ing)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method = "Matrix Factorization
",
                                     RMSE = matrix_decomp_model_rms
e))
rmse_results %>% kable
```

```
|method                                               |      RMSE
|
|:----------------------------------------------------|---------:
|
|Just the average                                     | 1.0602472
|
|Movie effect model                                   | 0.9435966
|
|Regularized movie effect model, lambda = 2.75        | 0.9435107
|
|Regularized movie and user effects model, lambda2 = 5 | 0.8654773
|
|Matrix Factorization                                 | 0.8652532
|
```

In [66]:
```
# --- NAIVE BAYES CLASSIFICATION ----------------------------------
-----

cols <- c("userId", "movieId", "rating", "genres")
predictions[,cols] <- data.frame(apply(predictions[cols], 2, as.fac
tor))
```

In [67]:
```
# Note: This process could take several minutes

library(e1071)

nb_fit <- naiveBayes(rating ~ userId + movieId + genres + resids, d
ata = predictions[, -c(4:5, 7:10)], laplace = 1e-3)
nb_pred <- predict(nb_fit, predictions[, -c(3:5, 7:10)])
```

In [68]:
```
# --- ACCURACY ----------------------------------------------------
-----

val_nb <- predictions %>% mutate(nb_pred)

matches_nb <- val_nb[val_nb$rating == val_nb$nb_pred,]
accuracy_nb <- round((nrow(matches_nb)/nrow(val_nb))*100, 2)

cat("The accuracy with the test set is", accuracy_nb)
```

```
The accuracy with the test set is 69.27
```

Although the assumption of independence of the predictor variables is not fulfilled here, we can see that naive Bayes actually does a good job in practice!

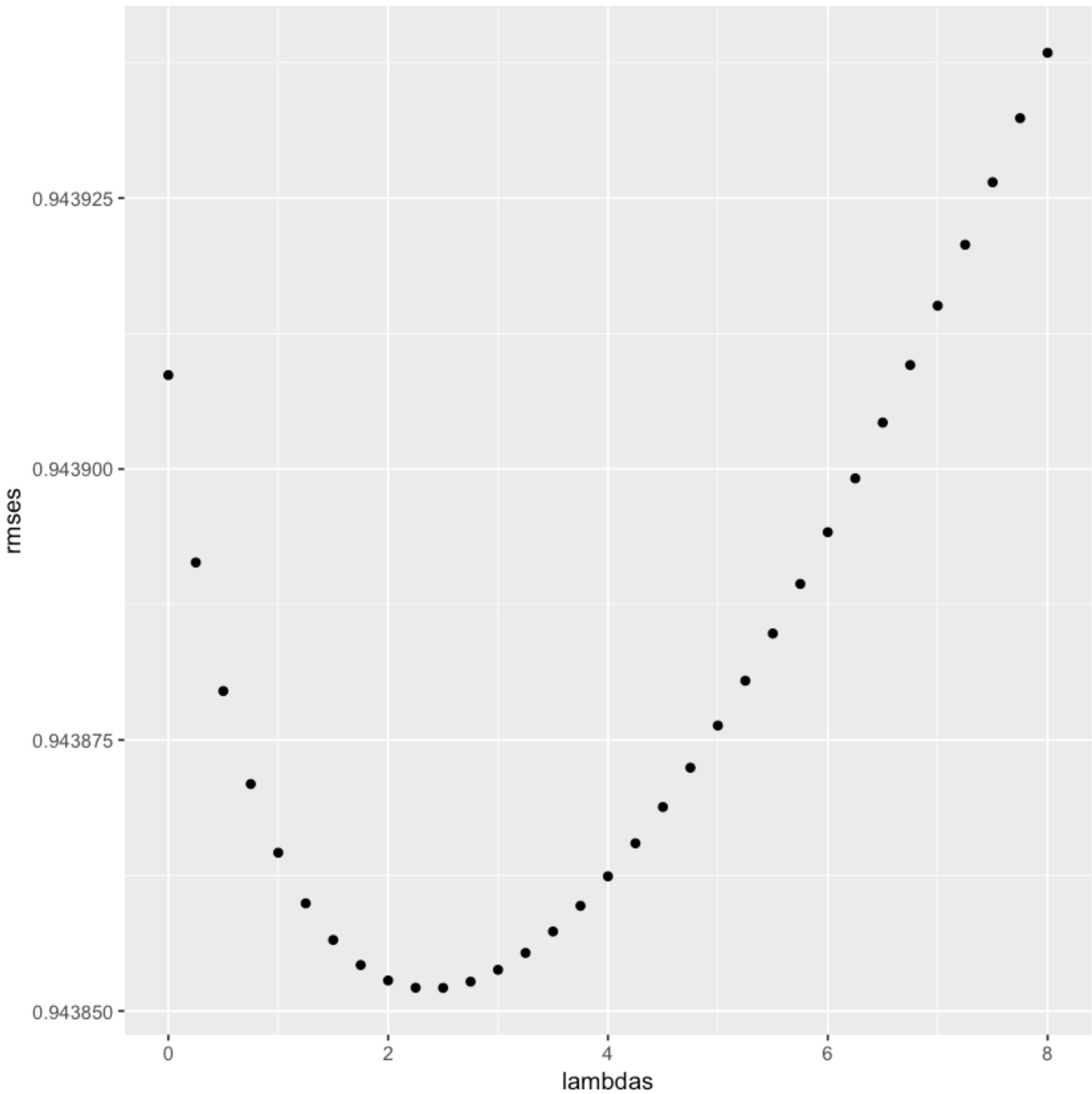
In [71]:
```
# Clean up memory
rm(test_index, train_set, test_set,
   RMSE, mu, predictions, naive_rmse,
   rmse_results, movie_means, joined, predicted_ratings, model1_rms
e,
   lambdas, tmp, rmses, lambda, movie_reg_means, model1_reg_rmse,
   lambdas_2, lambda_2, user_reg_means, model2_reg_rmse,
   new_train_set, var_explained, k, interaction, matrix_decomp_mode
l_rmse,
   cols, nb_fit, nb_pred, val_nb, matches_nb, accuracy_nb)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11698142	624.8	38831430	2073.9	38831430	2073.9
Vcells	91449333	697.8	6034406638	46038.9	6284171678	47944.5

Validation

In [72]:
```
# --- REGULARIZATION OF THE MOVIE EFFECT --------------------

# Compute regularized estimates of b_i using lambda. Let's first tr
y a few values of lambda and pick the best one.
lambdas <- seq(0, 8, 0.25)

mu <- mean(edx$rating)

tmp <- edx %>%
  group_by(movieId) %>%
  summarize(sum = sum(rating - mu), n_i = n())

rmses <- sapply(lambdas, function(l){
  joined <- validation %>%
    left_join(tmp, by='movieId') %>%
    mutate(b_i = sum/(n_i+l))
    predicted_ratings <- mu + joined$b_i
    return(RMSE(predicted_ratings, validation$rating))
})

cat("The best lambda (which minimizes the RMSE) for the movie effec
t is:", lambdas[which.min(rmses)])

qplot(lambdas, rmses)
```

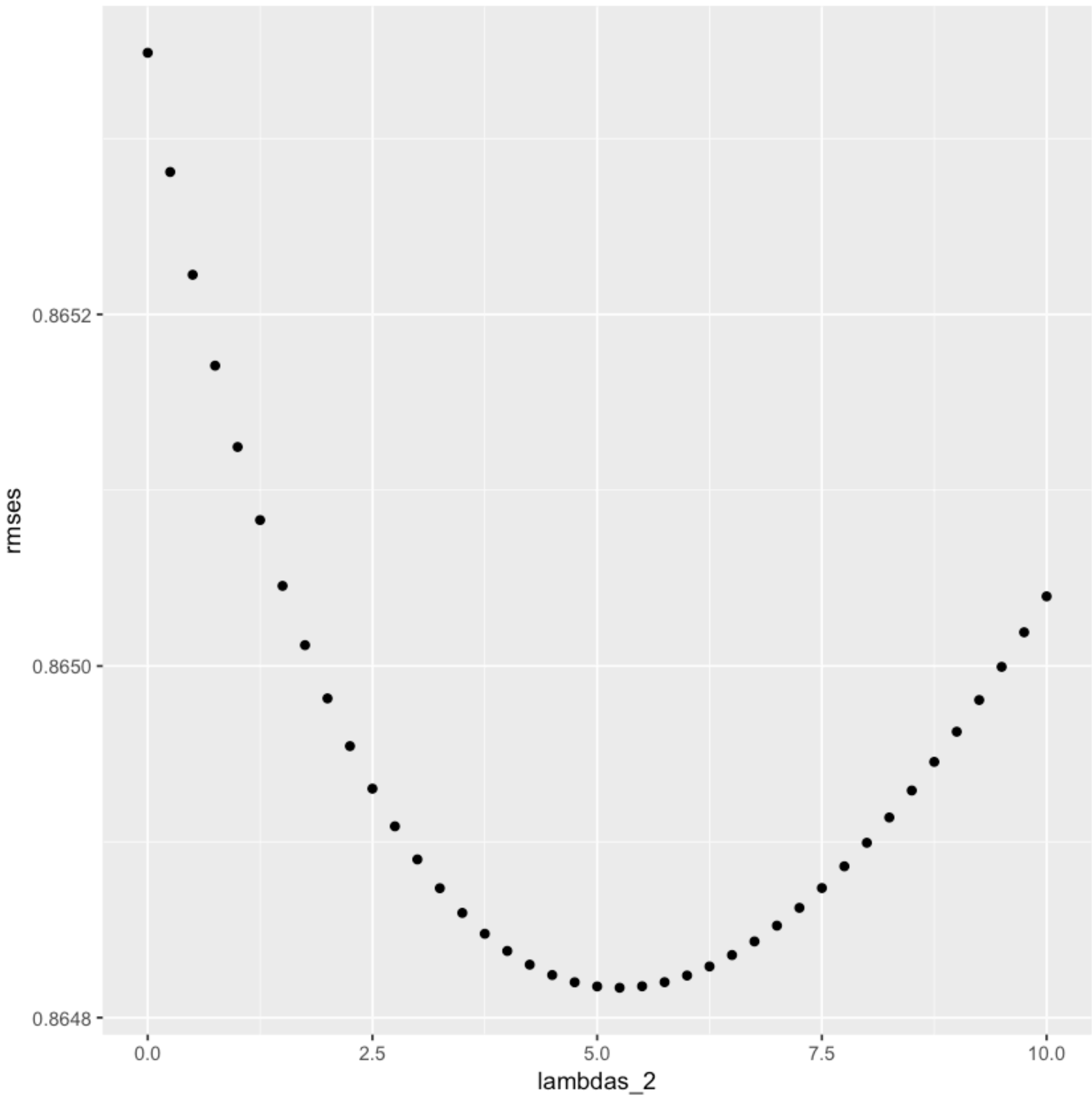
```
The best lambda (which minimizes the RMSE) for the movie effect is
: 2.5
```



In [73]:
```
# So it looks like a value of lambda = 2.5 gives us the smallest RM
SE

lambda <- 2.5

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

joined <- validation %>%
  left_join(movie_reg_means, by='movieId') %>%
  replace_na(list(b_i=0))

predicted_ratings <- mu + joined$b_i

model1_reg_rmse <- RMSE(predicted_ratings, validation$rating)

# Create a table that's going to store the results that we obtain a
s we're goinng to compare different effects.
rmse_results <- data_frame(method = "Regularized movie effect model
, validation",
                                     RMSE = model1_reg_rmse )
```

In [74]:
```
# --- REGULARIZATION OF THE USER AND MOVIE EFFECTS ----------

# Compute regularized estimates of b_i using lambda_2. Let's first
try a few values of lambda_2 and pick the best one.

lambdas_2 <- seq(0, 10, 0.25)

rmses <- sapply(lambdas_2, 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) %>%
    .$pred

    return(RMSE(predicted_ratings, validation$rating))
})

cat("The best lambda_2 (which minimizes the RMSE) for the user and
movie effects is", lambdas_2[which.min(rmses)])

qplot(lambdas_2, rmses)
```

```
The best lambda_2 (which minimizes the RMSE) for the user and movi
e effects is 5.25
```



In [75]:
```
# So it looks like a value of lambda_2 = 5.25 gives us the smallest
RMSE

lambda_2 <- 5.25

user_reg_means <- edx %>%
  left_join(movie_reg_means) %>%
  mutate(resids = rating - mu - b_i) %>%
  group_by(userId) %>%
  summarize(b_u = sum(resids)/(n()+lambda_2))

joined <- validation %>%
  left_join(movie_reg_means, by='movieId') %>%
  left_join(user_reg_means, by='userId') %>%
  replace_na(list(b_i=0, b_u=0))

predicted_ratings <- mu + joined$b_i + joined$b_u

model2_reg_rmse <- RMSE(predicted_ratings, validation$rating)

rmse_results <- bind_rows(rmse_results,
                          data_frame(method = "Regularized movie an
d user effects model, validation",
                                     RMSE = model2_reg_rmse ))
rmse_results %>% kable
```

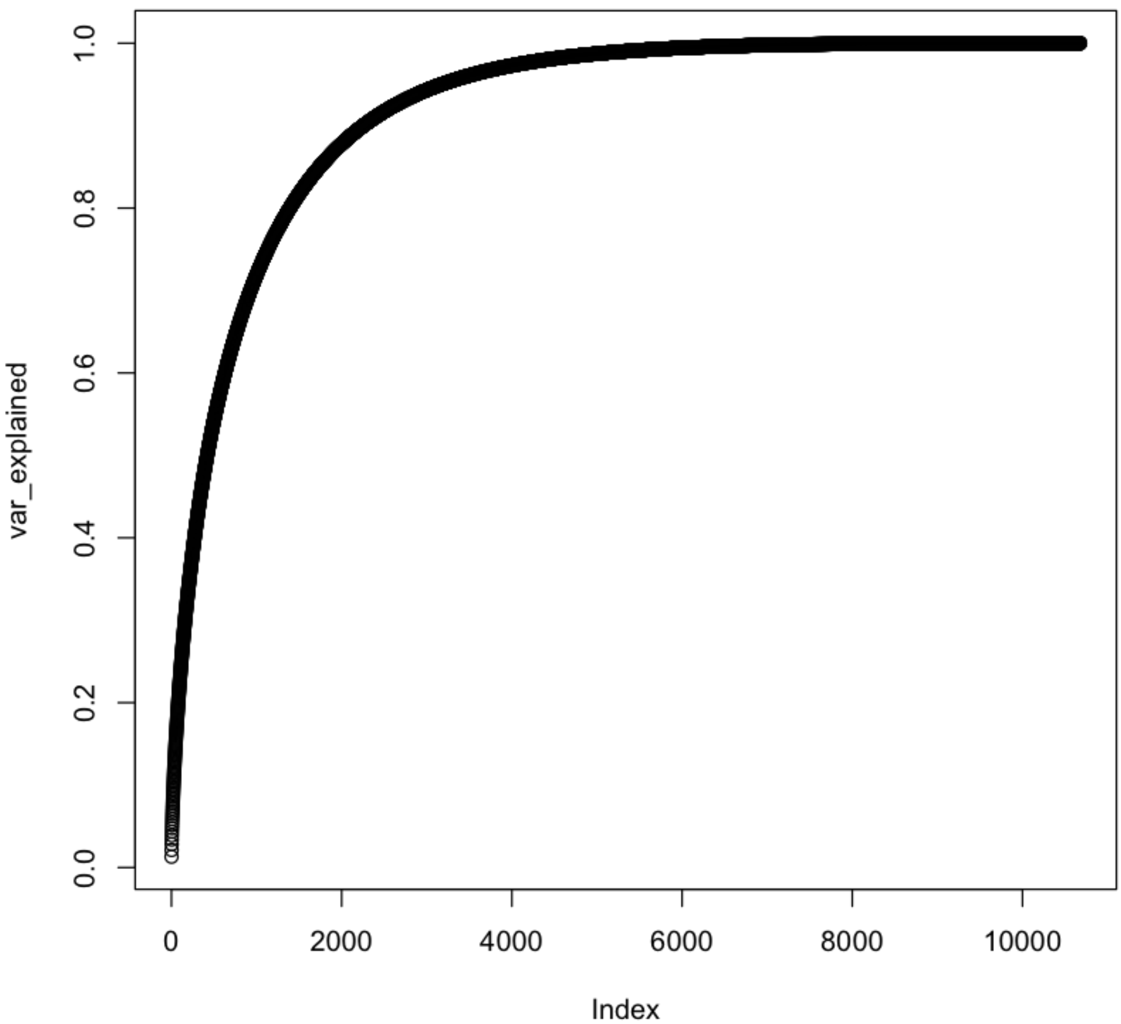
```
Joining, by = "movieId"


|method                                                |      RMSE|
|:-----------------------------------------------------|---------:|
|Regularized movie effect model, validation            | 0.9438521|
|Regularized movie and user effects model, validation  | 0.8648427|
```

In [76]:
```
# --- MATRIX DECOMPOSITION ----------------------------------------
-----

# We use PCA to uncover patterns in user/movie relationships

# First, tet's remove the user and movie bias to create residuals
new_edx <- edx %>%
  left_join(movie_reg_means, by = "movieId") %>%
  left_join(user_reg_means, by = "userId") %>%
  mutate(resids = rating - mu - b_i - b_u)
```

In [77]:
```
# Next we create a matrix using spread()
# Note: This process could take several minutes

r <- new_edx %>%
  select(userId, movieId, resids) %>%
  spread(movieId, resids) %>%
  as.matrix()

rownames(r) <- r[,1]
r <- r[,-1]
r[is.na(r)] <- 0 # For the sake of simplicity, we just apply 0 to a
ll missing data
```

In [78]:
```
# Singular value decomposition
# Note: This process could take several long minutes

pca <- prcomp(r - rowMeans(r), center = TRUE, scale = FALSE)
```

In [79]:
```
# Variability
var_explained <- cumsum(pca$sdev^2/sum(pca$sdev^2))
plot(var_explained)
```



In [80]:
```
# Factorization of the 4000 first principal components, which expla
in almost all the variability

k <- 4000

pred <- pca$x[,1:k] %*% t(pca$rotation[,1:k])
colnames(pred) <- colnames(r)
```

In [81]:
```
# Note: This process could take several very long minutes

interaction <-
    data.frame(userId = as.numeric(rownames(r)), pred, check.names
= FALSE) %>%
    tbl_df %>%
    gather(movieId, b_ui, -userId) %>%
    mutate(movieId = as.numeric(movieId))
```

In [82]:
```
# Clean up memory
rm(pred, pca, r)
gc()
```

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	11699056	624.8	38831430	2073.9	38831430	2073.9
Vcells	2414885247	18424.2	7513794689	57325.8	6284171678	47944.5

In [83]:
```
# Note: This process could take several very long hours

joined <- validation %>%
  left_join(movie_reg_means, by='movieId') %>%
  left_join(user_reg_means, by='userId') %>%
  left_join(interaction, by=c('movieId','userId')) %>%
  replace_na(list(b_i=0, b_u=0, b_ui=0))

predictions <- joined %>% mutate(resids = rating - mu - joined$b_i
- joined$b_u - joined$b_ui)
head(predictions)
```

userId	movieId	rating	timestamp	title	genres	b_i
1	231	5	838983392	Dumb & Dumber (1994)	Comedy	-0.57725
1	480	5	838983653	Jurassic Park (1993)	Action|Adventure|Sci-Fi|Thriller	0.151043
1	586	5	838984068	Home Alone (1990)	Children|Comedy	-0.45673
2	151	3	868246450	Rob Roy (1995)	Action|Drama|Romance|War	0.017587
2	858	2	868245645	Godfather, The (1972)	Crime|Drama	0.902773
2	1544	3	868245920	Lost World: Jurassic Park, The (Jurassic Park 2) (1997)	Action|Adventure|Horror|Sci-Fi|Thriller	-0.56699

In [84]:

```
predicted_ratings <- mu + predictions$b_i + predictions$b_u + predi
ctions$b_ui

matrix_decomp_model_rmse <- RMSE(predicted_ratings, predictions$rat
ing)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method = "Matrix Factorization
, validation",
                                     RMSE = matrix_decomp_model_rms
e))
rmse_results %>% kable
```

```
|method                                           |      RMSE|
|:------------------------------------------------|---------:|
|Regularized movie effect model, validation       | 0.9438521|
|Regularized movie and user effects model, validation | 0.8648427|
|Matrix Factorization, validation                 | 0.8644608|
```

In [85]:

```
# --- NAIVE BAYES CLASSIFICATION -----------------------------------
-----

cols <- c("userId", "movieId", "rating", "genres")
predictions[,cols] <- data.frame(apply(predictions[cols], 2, as.fac
tor))
```

In [86]:
```
# Note: This process could take several minutes

nb_fit <- naiveBayes(rating ~ userId + movieId + genres + resids, d
ata = predictions[, -c(4:5, 7:10)], laplace = 1e-3)
nb_pred <- predict(nb_fit, predictions[, -c(3:5, 7:10)])
```

In [87]:
```
# --- ACCURACY -----------------------------------------------------
-----

val_nb <- predictions %>% mutate(nb_pred)

matches_nb <- val_nb[val_nb$rating == val_nb$nb_pred,]
accuracy_nb <- round((nrow(matches_nb)/nrow(val_nb))*100, 2)

cat("The accuracy with the validation set is", accuracy_nb)
```

```
The accuracy with the validation set is 71.07
```

5. Conclusion

In this project, we started with an exploratory analysis of the data, which provided interesting insights such as:

- The edx dataset as provided is already curated, ready to use. No missing values, no wrong formatting, no much data engineering is required.
- the dataset contains 2 parts of about equally sizes, one set before 18 February 2003 with full star rating from 1 star to 5 stars by increment of 1 star and another set after that date with 0.5 star increment for a range from 0.5 star to 5 stars.
- The overall average of ratings, at about 3.5 stars, is rather consistent over the whole dataset.
- There is a clear dependence between users and movies for ratings. There is a correlation pattern (users have preferences of movies) that should be taken into account during the modeling.
- The effect of various sample sizes in ratings. So this also needs to be considered in our model.

Other insights about best movies, most popular genres, movies production, are more for general information.

Following the exploratory phase, we built our predictive model based on a blend of **regularized user and movie effects** and **matrix factorization**. In the matrix factorization, we used a Principal Component Analysis approach to uncover the user/movie interactions. The final step was to call a **naive Bayes** model to classify our predicted ratings in the range of 0.5 star to 5 stars with increment of 0.5 star and estimate the accuracy or our predictions.

1. RMSE metric.

Our predictive model yields a very good RMSE. The RMSEs at the various steps of our blend of techniques are summarized in the table below:

Method	RMSE

Movie effect with regularization	0.9439
User and movie effects with regularization	0.8648
Matrix factorization	0.8645

2. Accuracy metric.

The accuracy metric implies first a classification of our predicted ratings, which are continuous variables, into class of ratings and the naive Bayes did perform amazingly well.

The final accuracy, with the validation set, reaches 71.1%.

Note that we tried to call naive Bayes on separated sets, before and after 18 Feb 2003. The small accuracy improvement is not worth mentioning in this report. Naive Bayes performs very well on the whole dataset.

3. Important note:

We believe the RMSE metric is optimized but we could possibly improve the accuracy metric with more sophisticated classifiers, for example based on Nearest Neighbors approach.

Nevertheless, we couldn't move forward with sophisticated models, due to the size of our dataset and the limited machine resources allocated to this project.