MovieLens Recommender System Capstone Project - Report

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Contents

1 Executive Summary

The purpose for this project is creating a movie recommendation system using MovieLens dataset.

The version of movielens dataset used for this final assignment contains approximately 10 Milions of movies ratings, divided in 8.5 Milions for training and 1.5 Milion for validation or testing. It is a small subset of a much larger dataset with several millions of ratings. Into the training dataset there are approximately

70.000 users and **11.000 different movies** divided in 20 genres such as Action, Adventure, Horror, Drama,Thriller and more.

After a initial data exploration, the recommender systems built on this dataset are evaluated and chosen

based on the RMSE - Root Mean Squared Error that should be at least lower than **0.8649**.

For accomplishing this goal, the **Movie+User Model** is capable to reach a RMSE of **0.863**, that is really good.

2 Method and Analysis

2.1 Inital data Exploration

The 10 Millions dataset is divided into two dataset: edx for training purpose and validation for the validation phase.

The edx dataset contains approximately 9 Millions of rows with 70.000 different users and 11.000 movies with rating score between 0.5 and 5. There is no missing values (0 or NA).

	Users	Movies
	<int>	*<int>*
1	69878	10677

The features/variables/columns in both datasets are six:

- **userId** (class integer) Unique user identification number .
- **movieId** (class numeric) Unique movie identification number
- **rating** (class numeric) One user‘s rating of one movie. Ratings are given out of a 5(1,1.5,2…)
- **timestamp** (class integer) Timestamp for one particular rating by one particular user.
- **title** (class character) Title of each movie with the release year.
- **genres** (class character) list of genres of each movie separated by pipe(|).

First 6 Rows of edx dataset

	movieId	title	year	genres
1	31	Dangerous Minds	1995	Drama
2	1029	Dumbo	1941	Animation|Children|Drama|Musical
3	1061	Sleepers	1996	Thriller
4	1129	Escape from New York	1981	Action|Adventure|Sci-Fi|Thriller
5	1172	Cinema Paradiso (Nuovo cinema Paradiso)	1989	Drama
6	1263	Deer Hunter	1978	Drama|War

	userId	rating	timestamp
1	1	2.5	1260759144
2	1	3.0	1260759179
3	1	3.0	1260759182
4	1	2.0	1260759185
5	1	4.0	1260759205
6	1	2.0	1260759151

2.2 Dataset Pre-Processing and Feature Engineering

After some initial data exploration, we see that each movie has many different genres. It's necessary to extract and separate them for better consistency. We also notice that the title contains the year of the movie release which can be made into a separate column in the data frame to be used for further analysis. Finally, we can obtain the year and the month for each rating from the timestamp column.

The pre-processing phase is comprised of the following:
1. Format timestamp to a human readable date
2. Extract the month and the year from the date
3. Extract the release year from the title
4. Separate each genre from the list of genres of each movie. It increases the size of both datasets.

After preprocessing the data, edx dataset looks like this:

Processed edx datadaset

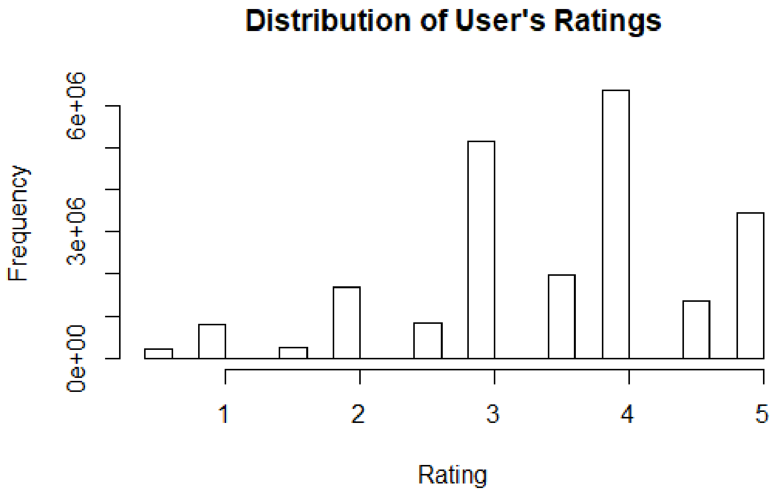
	userId	movieId	rating	title	release	year_rated	month_rated	genre
	<int>	*<dbl>*	*<dbl>*	*<chr>*	*<int>*	*<dbl>*	*<dbl>*	*<chr>*
1	1	122	5	Boomerang (1992)	1992	96	8	Comedy
2	1	122	5	Boomerang (1992)	1992	96	8	Romance
3	1	185	5	Net, The (1995)	1995	96	8	Action
4	1	185	5	Net, The (1995)	1995	96	8	Crime
5	1	185	5	Net, The (1992)	1995	96	8	Thriller

2.3 Rating frequency Distributions:

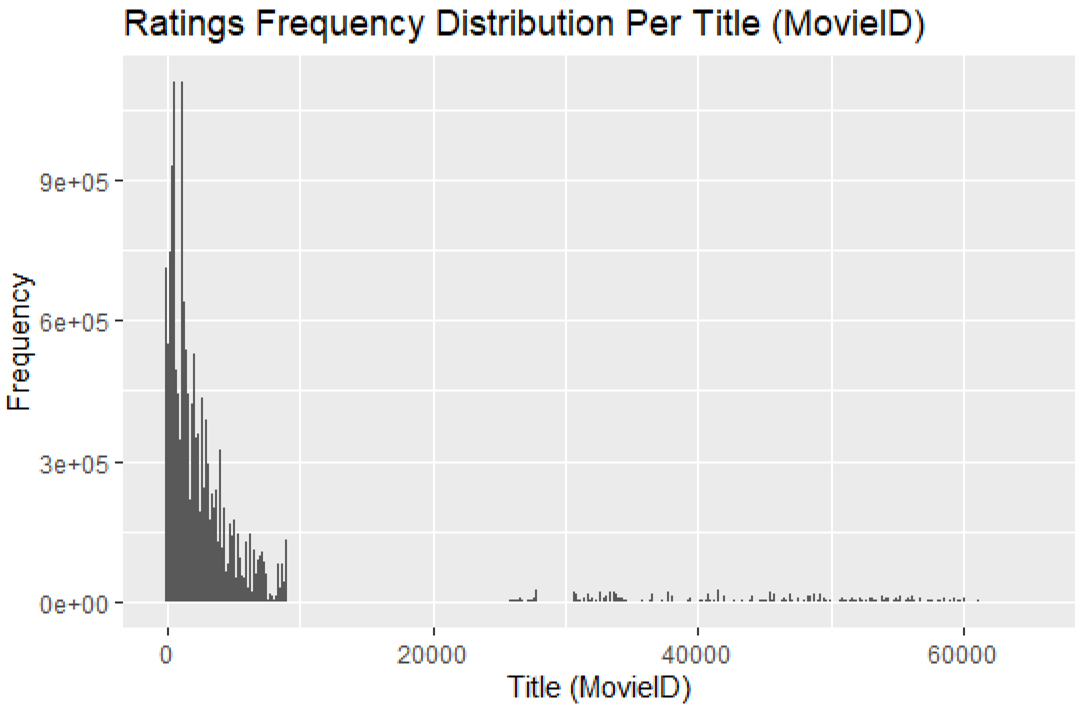
Overview of Rating Distribution

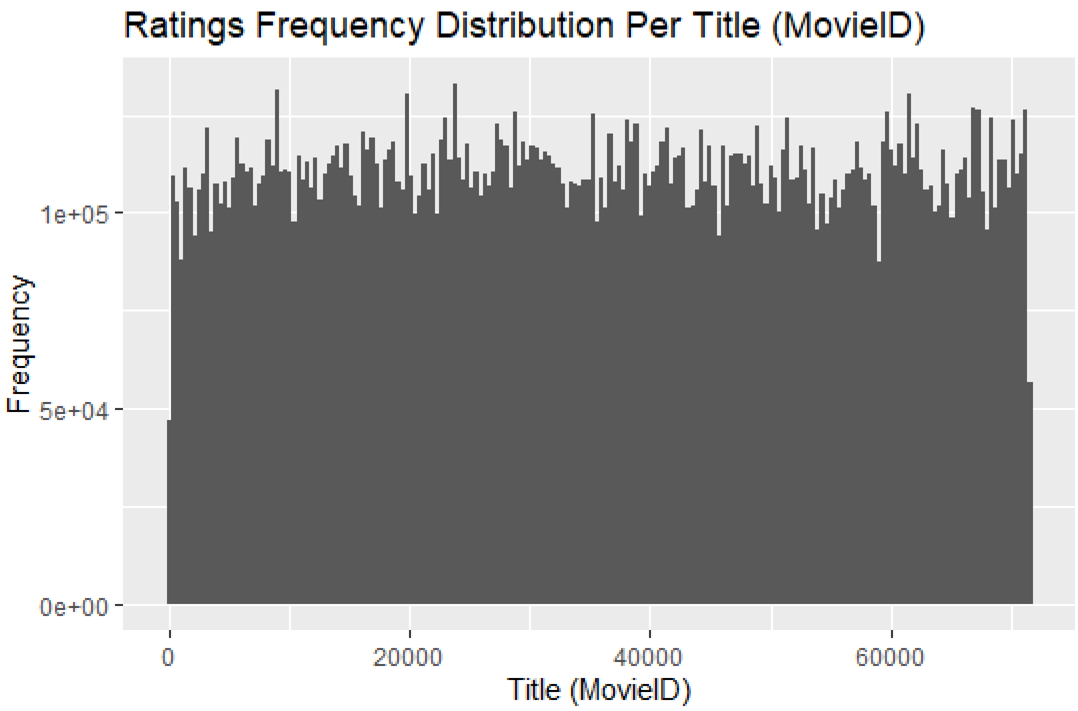
According to the given histogram, it can be seen that there are a small number of negative votes. It is noticed that half-Star votes are rarer than "Full-Star" votes.

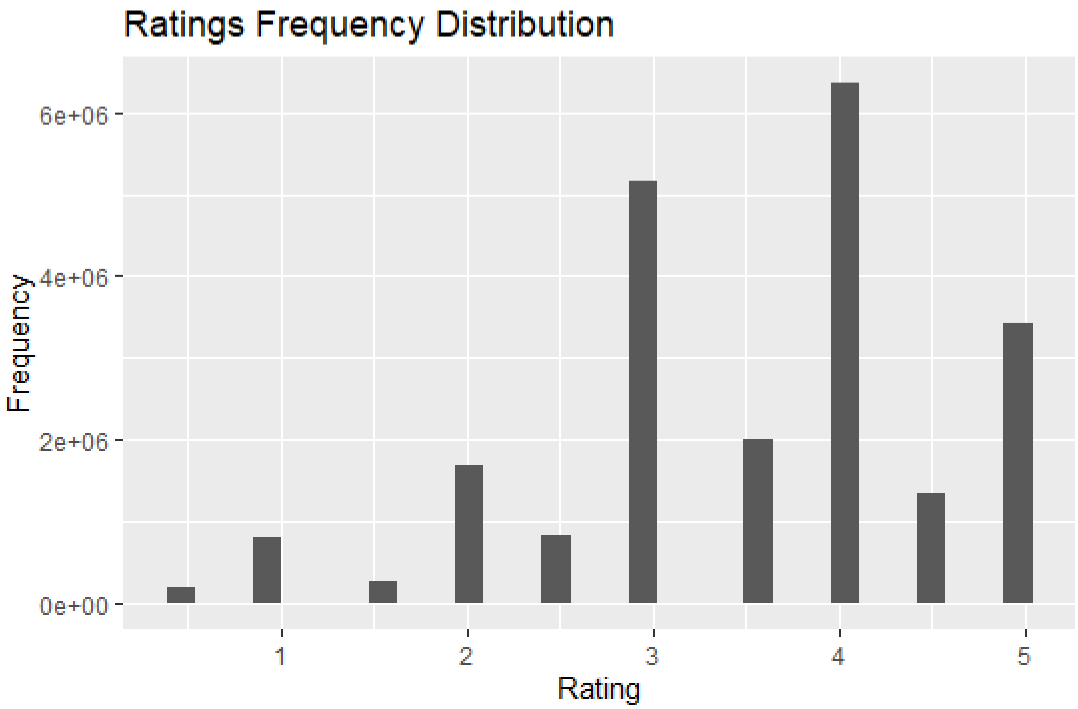
Distribution of User Ratings

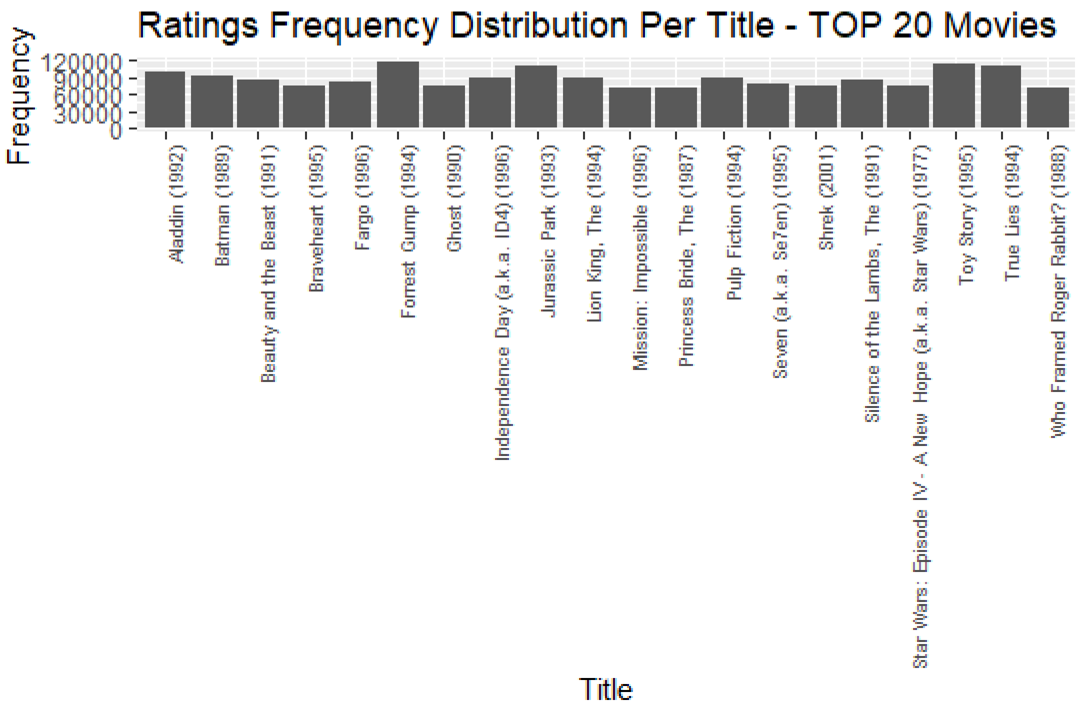


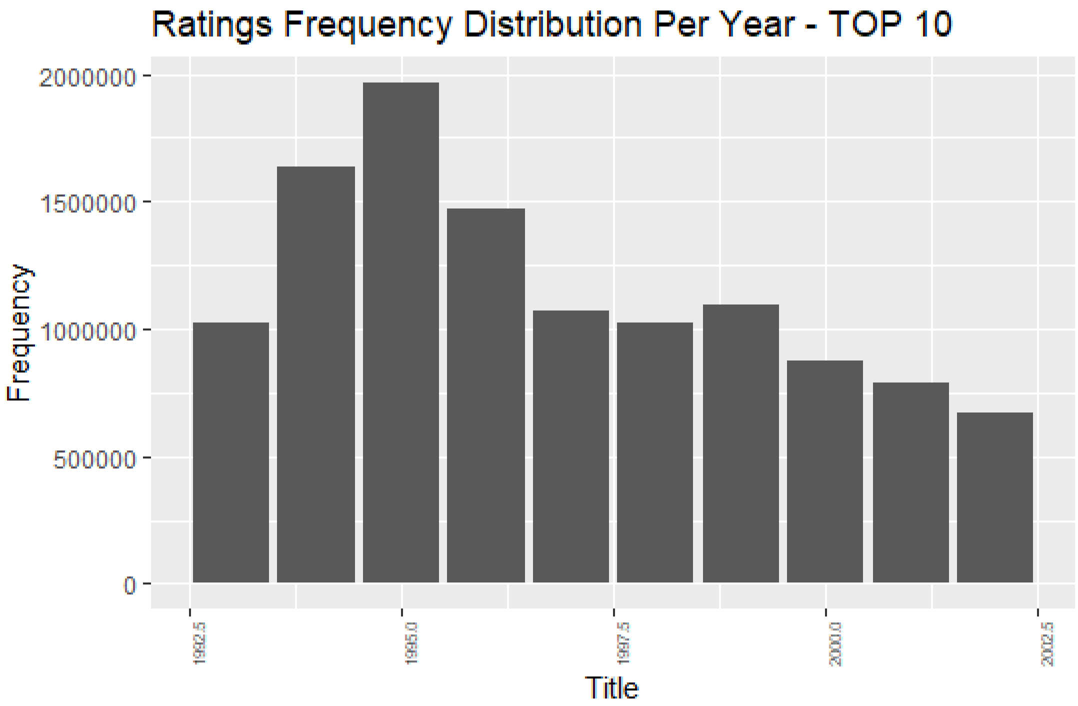
Rating frequency Distribution of User Ratings per Title

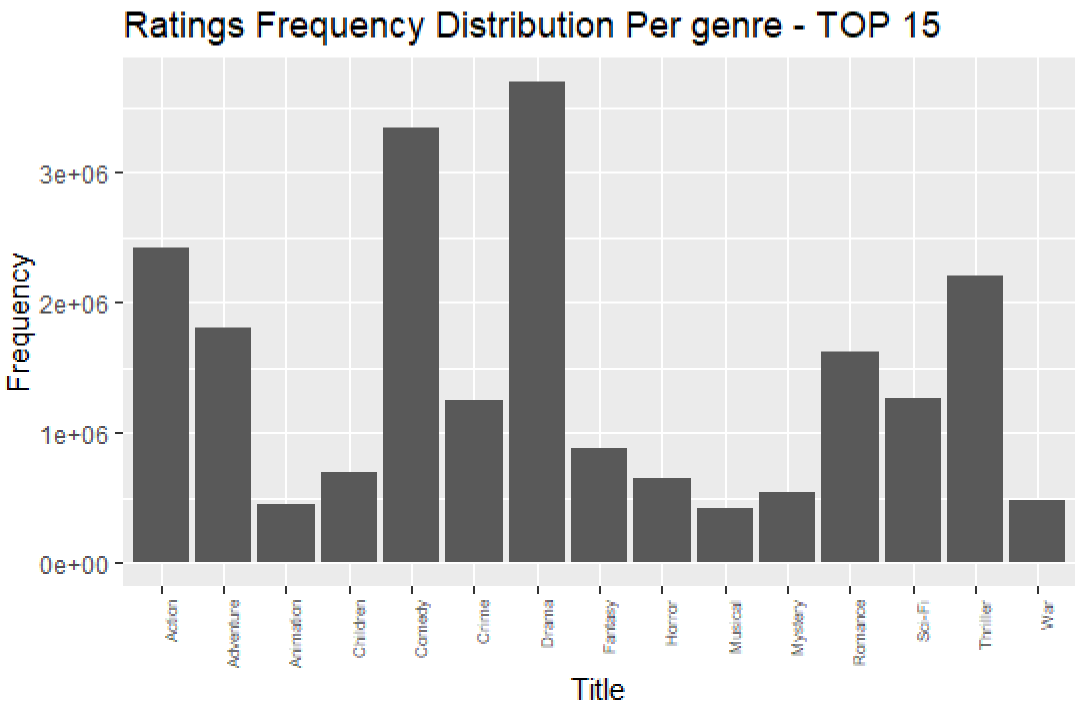



Ratings Frequency Distribution Per Title (MovieID)
Frequency
1e+05
5e+04
0e+00
0
20000
40000
60000
Title (MovieID)


Ratings Frequency Distribution
Frequency
6e+06
4e+06
2e+06
0e+00
1
2
3
4
5
Rating


Ratings Frequency Distribution Per Title - TOP 20 Movies
Frequency
120000
90000
60000
30000
0
Aladdin (1992)
Batman (1989)
Beauty and the Beast (1991)
Braveheart (1995)
Fargo (1996)
Forrest Gump (1994)
Ghost (1990)
Independence Day (a.k.a. ID4) (1996)
Jurassic Park (1993)
Lion King, The (1994)
Mission: Impossible (1996)
Princess Bride, The (1987)
Pulp Fiction (1994)
Seven (a.k.a. Se7en) (1995)
Shrek (2001)
Silence of the Lambs, The (1991)
Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977)
Toy Story (1995)
True Lies (1994)
Who Framed Roger Rabbit? (1988)
Title


Ratings Frequency Distribution Per Year - TOP 10
Frequency
2000000
1500000
1000000
500000
0
1992.5
1995.0
1997.5
2000.0
2002.5
Title



Rating frequency distribution per title(top 10)

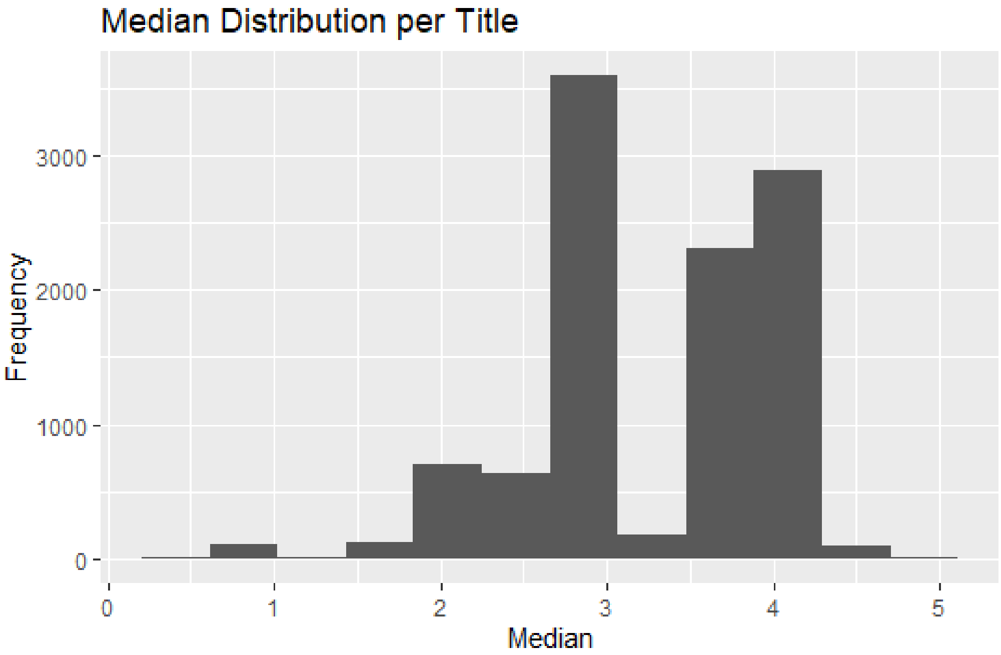
```
title                                    count
   <chr>                                 <int>
 1 Forrest Gump (1994)                   117180
 2 Toy Story (1995)                      112450
 3 Jurassic Park (1993)                  111016
 4 True Lies (1994)                      107790
 5 Aladdin (1992)                        99880
 6 Batman (1989)                         91788
 7 Pulp Fiction (1994)                   89058
 8 Lion King, The (1994)                 89005
 9 Independence Day (a.k.a. ID4) (1996)  88848
10 Silence of the Lambs, The (1991)      85665
```

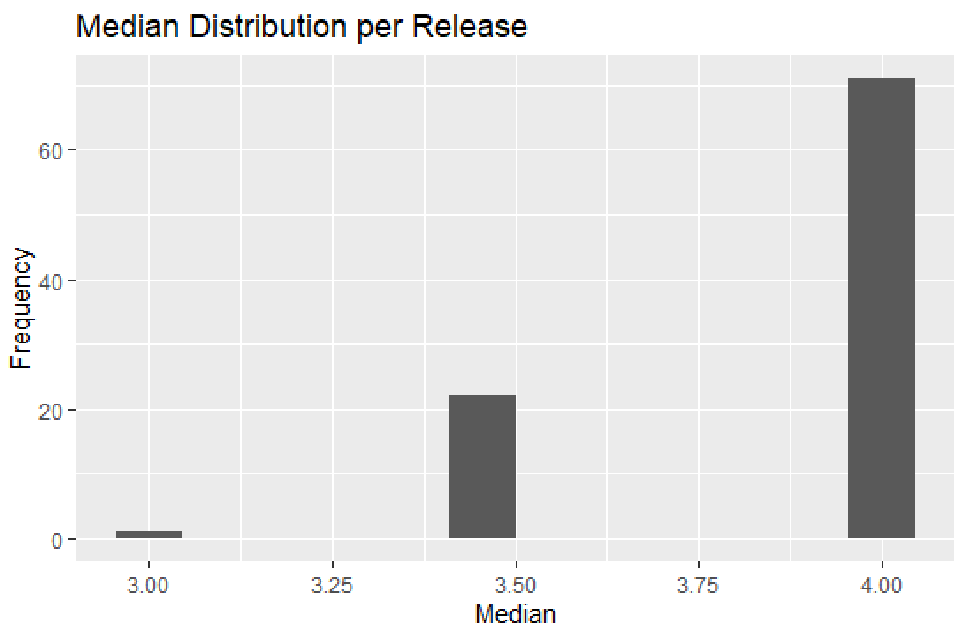
Rating frequency distribution per year

```
release          count
   <int>         <int>
 1   1995        1968372
 2   1994        1635409
 3   1996        1475053
 4   1999        1094170
 5   1997        1074284
 6   1998        1025660
 7   1993        1025377
 8   2000        878117
 9   2001        786606
10    2002       671877
```

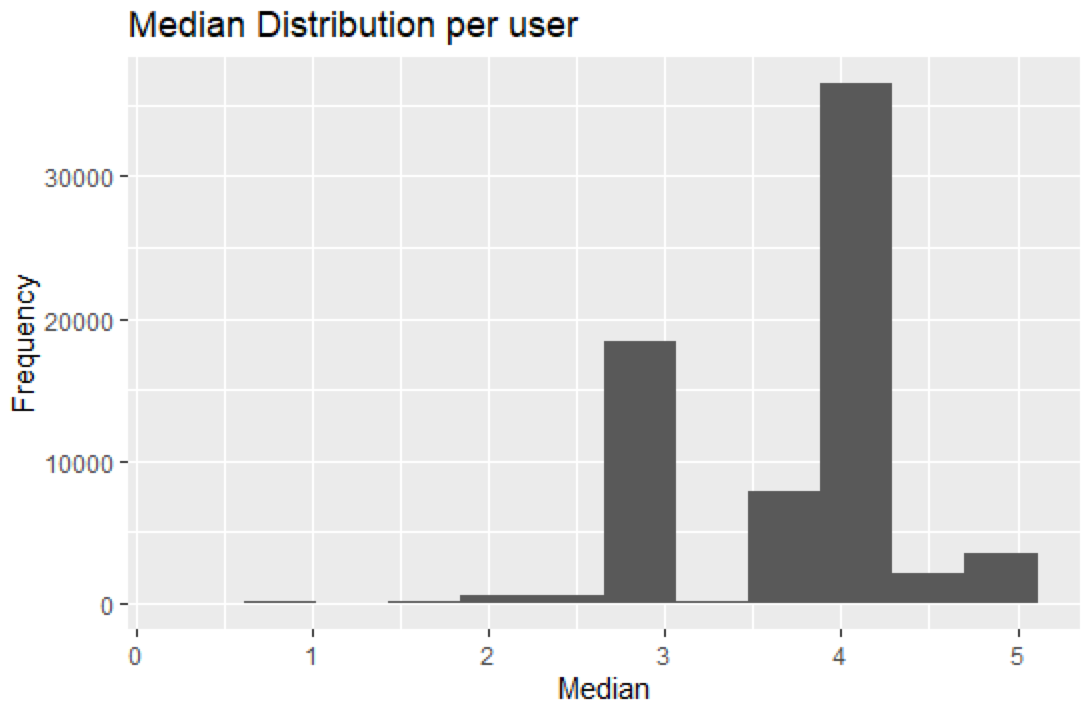
Median rating Distributions

Median rating distribution histograms





Median Distribution per Release



Median Distribution per user

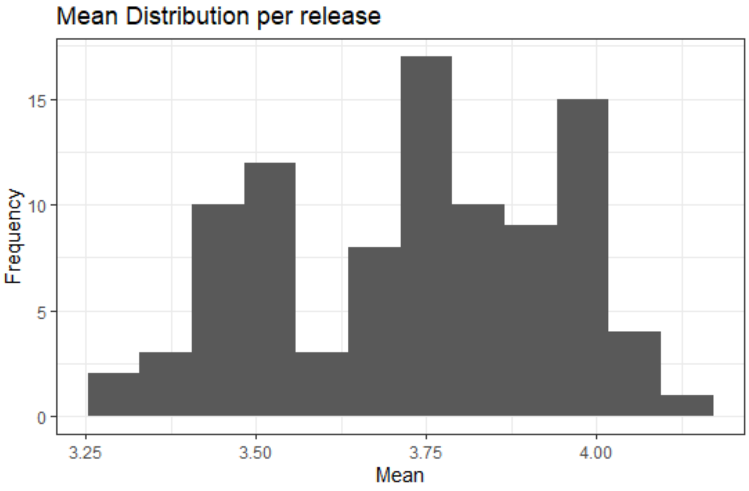
Median rating distribution tables

2.3.1 Median distribution per title(top 10)

```
title                                                  median
  <chr>                                                <dbl>
 1 Blue Light, The (Das Blaue Licht) (1932)            5
 2 Class, The (Entre les Murs) (2008)                  5
 3 Constantine's Sword (2007)                          5
 4 Fighting Elegy (Kenka erejii) (1966)                5
 5 Godfather, The (1972)                               5
 6 Kids of Survival (1996)                             5
 7 More (1998)                                         5
 8 Satan's Tango (SÃ¡tÃ¡ntangÃ³) (1994)                 5
 9 Shadows of Forgotten Ancestors (1964)               5
10 Shawshank Redemption, The (1994)                    5
```

Median distribution per year(top 10)

```
release                                                median
    <int>                                              <dbl>
 1   1916                                              4
 2   1918                                              4
 3   1920                                              4
 4   1921                                              4
 5   1922                                              4
 6   1923                                              4
 7   1924                                              4
 8   1925                                              4
 9   1926                                              4
10    1927                                             4
```

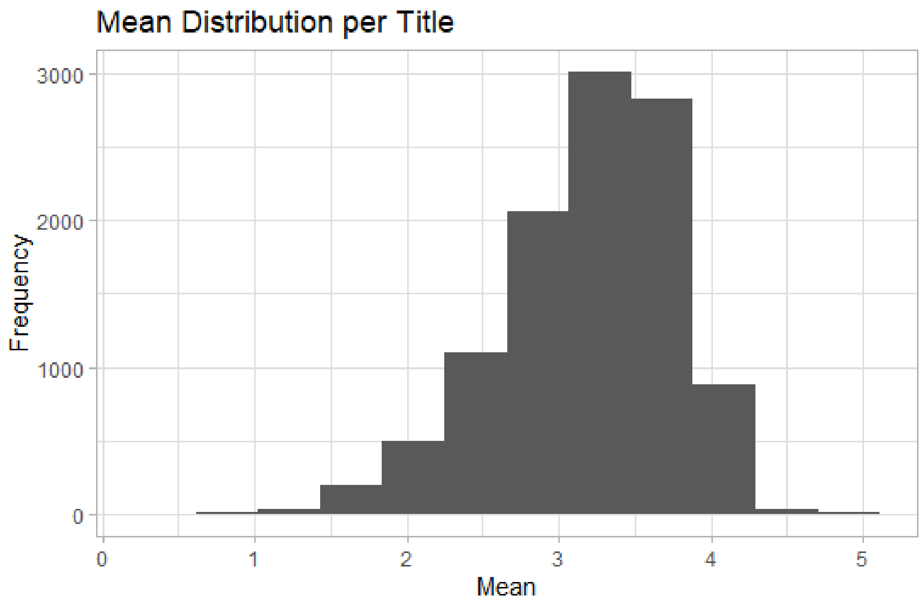


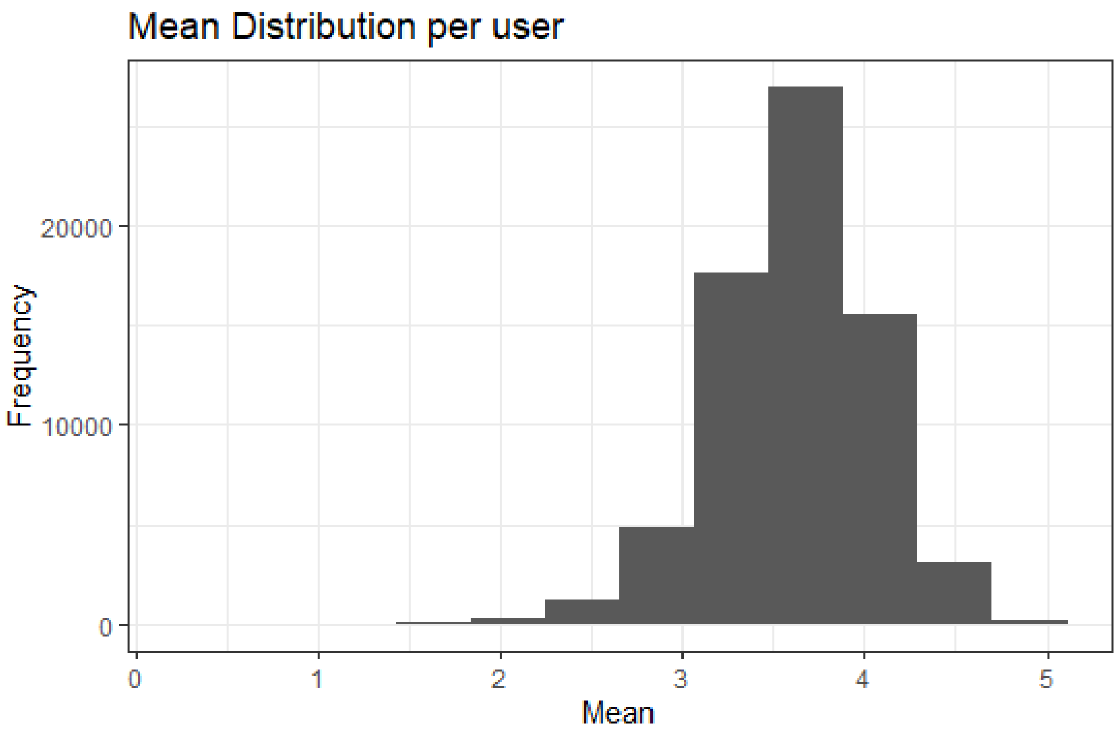
Median distribution per user(top 10)

	userId	median
	<int>	*<dbl>*
1	1	5
2	4	5
3	30	5
4	43	5
5	44	5
6	51	5
7	56	5
8	98	5
9	104	5
10	123	5

Mean Rating distributions

Mean Rating distribution histograms





Mean Rating Distribution Tables

Mean Rating Distribution Per Title (MovieID) - Top 10

```
   title                                                          mean
  <chr>                                                          <dbl>
 1 Blue Light, The (Das Blaue Licht) (1932)                      5
 2 Class, The (Entre les Murs) (2008)                            5
 3 Constantine's Sword (2007)                                    5
 4 Fighting Elegy (Kenka erejii) (1966)                          5
 5 Satan's Tango (SÃ¡tÃ¡ntangÃ³) (1994)                          5
 6 Shadows of Forgotten Ancestors (1964)                         5
 7 Sun Alley (Sonnenallee) (1999)                                5
 8 Sun Shines Bright, The (1953)                                 5
 9 Human Condition II, The (Ningen no joken II) (1959)           4.75
10 Human Condition III, The (Ningen no joken III) (1961)         4.75
```

Mean Rating Distribution Per Release Year- Top 10

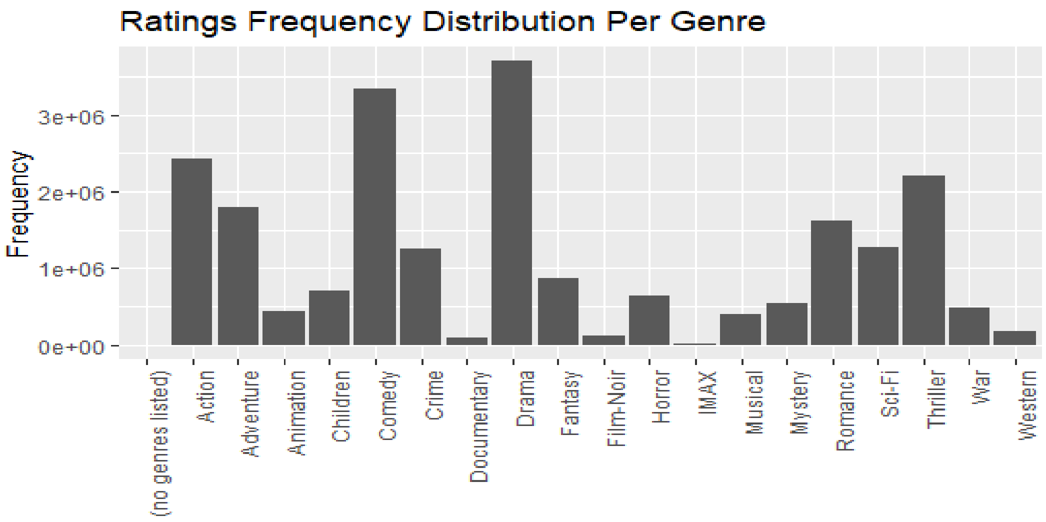
```
  release          mean
    <int>          <dbl>
 1   1931          4.11
 2   1934          4.08
 3   1946          4.06
 4   1944          4.05
 5   1957          4.03
 6   1927          4.01
 7   1942          4.00
 8   1952          4.00
 9   1949          4.00
10    1962         3.99
```

Mean Rating Distribution Per User ID- Top 10

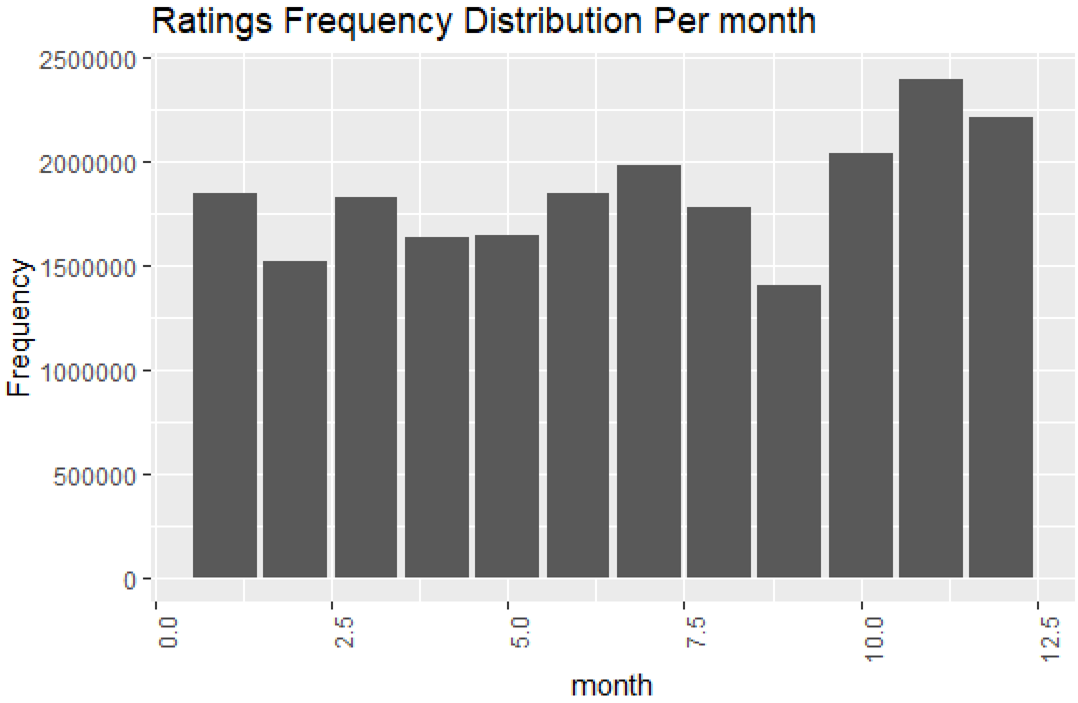
```
   userId          mean
   <int>           <dbl>
 1      1          5
 2   7984          5
 3  11884          5
 4  13027          5
 5  13513          5
 6  13524          5
 7  15575          5
 8  18965          5
 9  22045          5
10  26308          5
```

Genre Analysis

2.4. Rating Distribution per Genre



Rating Distribution per Month



Rating Distribution Tables

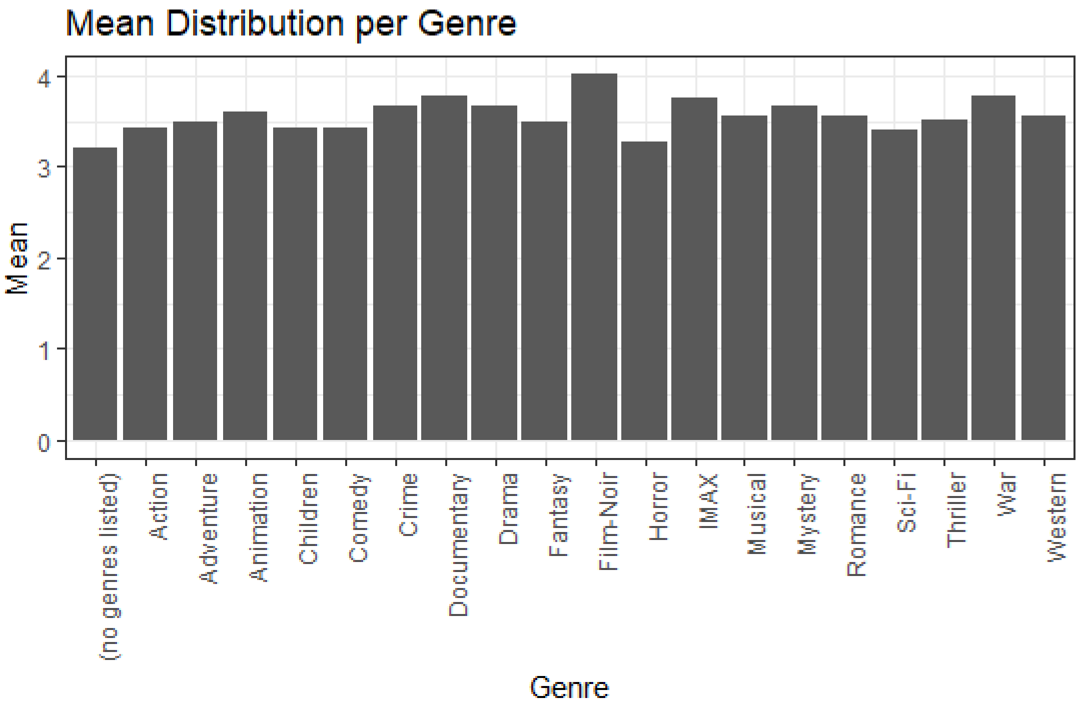
Ratings Frequency Distribution Per Genre

```
   genre                   count
   <chr>                   <int>
 1 Drama                   3693674
 2 Comedy                  3343505
 3 Action                  2418271
 4 Thriller                2197031
 5 Adventure               1802802
 6 Romance                 1616899
 7 Sci-Fi                  1267340
 8 Crime                   1254235
 9 Fantasy                 874268
10 Children                696914
11 Horror                  652597
12 Mystery                 537130
13 War                     482621
14 Animation               440852
15 Musical                 408685
16 Western                 178863
17 Film-Noir               112168
18 Documentary             87957
19 IMAX                    7739
20 (no genres listed)      5
```

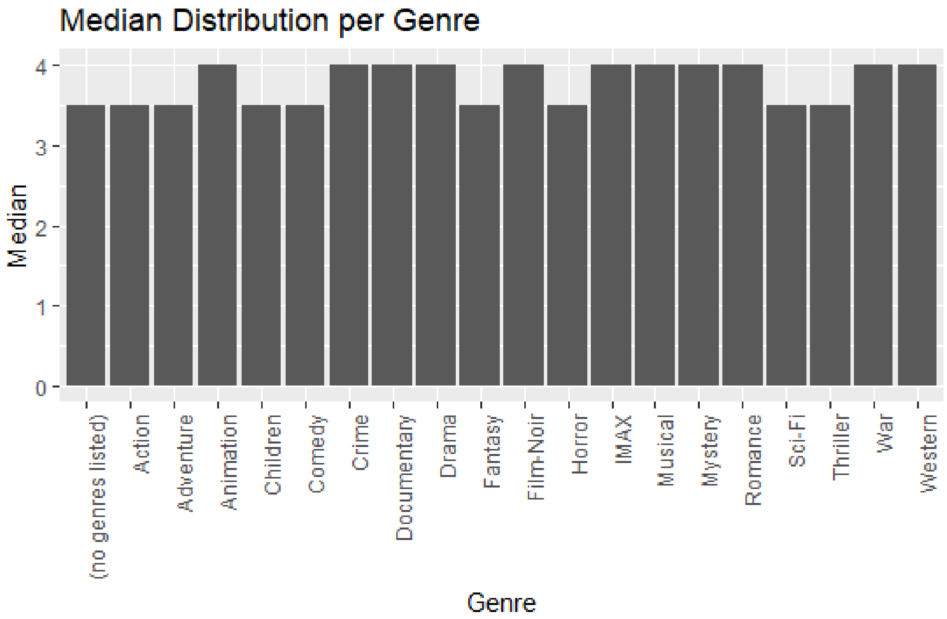
Ratings Frequency Distribution Per Month

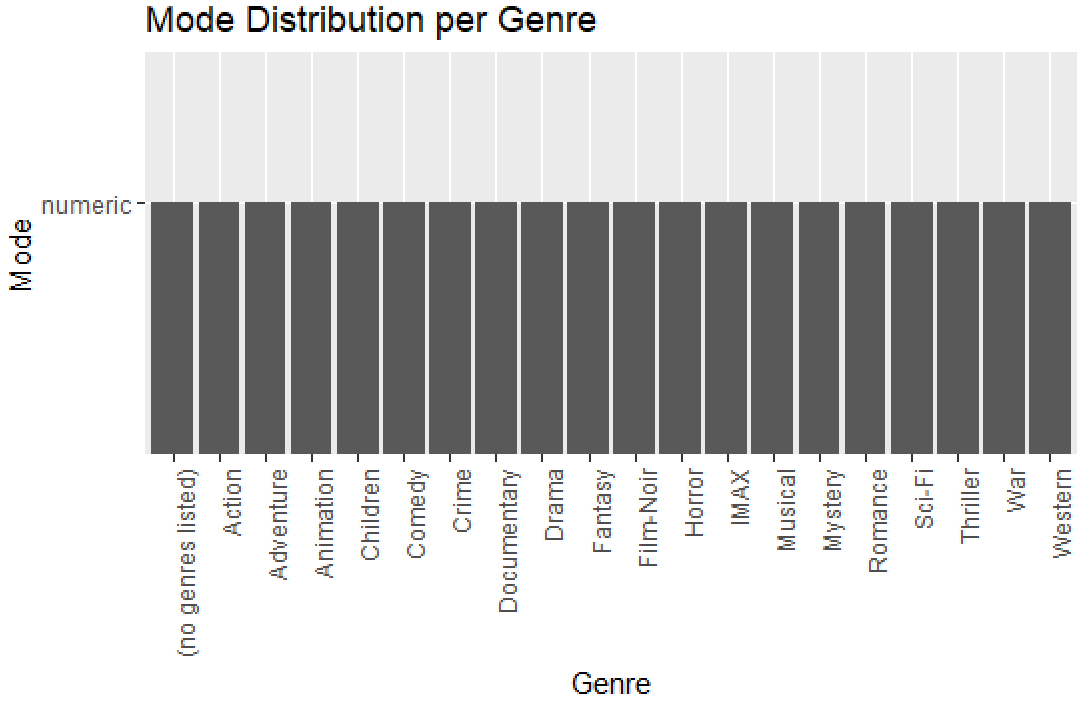
```
     month_rated            count
       <dbl>                <int>
 1       11                 2394359
 2       12                 2203980
 3       10                 2035272
 4        7                 1972738
 5        1                 1843616
 6        6                 1837634
 7        3                 1827162
 8        8                 1773138
 9        5                 1638183
10        4                 1633203
11        2                 1515358
12        9                 1398913
```

2.4.2 Mean Distribution per Genre



2.4.3 Median Distribution per Genre





Median distribution per genre

```
genre              median
  <chr>            <dbl>
 1 Animation       4
 2 Crime           4
 3 Documentary     4
 4 Drama           4
 5 Film-Noir       4
 6 IMAX            4
 7 Musical         4
 8 Mystery         4
 9 Romance         4
10 War             4
```

Mean distribution per genre

```
genre              mean
  <chr>            <dbl>
 1 Film-Noir       4.01
 2 Documentary     3.78
 3 War             3.78
 4 IMAX            3.76
 5 Mystery         3.68
 6 Drama           3.67
 7 Crime           3.67
 8 Animation       3.60
 9 Musical         3.56
10 Western         3.56
```

3 Analysis - Model Building and Evaluation

3.1 Naive Baseline Model

The simplest model possible, is a Naive Model that predicts the mean for all cases. In this case, the mean is **3.512465**, approximately **3.5**.

3.1.1 Naive Mean-Baseline Model

The formula used is:

Yu,i = ˆ*μ* + "*u,i*

With ˆ*µ* is the mean and *"i,u* is the independent errors sampled from the same distribution centered at 0.

Mu_hat is 3.527021 and the rmse on the validation set is **1.052698**, approximately **1.05**. It is larger than the target RMSE (below 0.87) and that indicates poor performance for the model.

3.2 Movie-Based Model, a Content-based Approach

The first Non-Naive Model takes into account the type of movie. In this case the movies that are rated higher or lower respect to each other.

The formula used is:

Yu,i = ˆ*µ* + *bi* + _*u,i*

With ˆ*µ* is the mean and *"i,u* is the independent errors sampled from the same distribution centered at 0. The *bi* is a measure for the popularity of movie *i*, i.e. the bias of movie *i*.

The RMSE on the validation dataset is **0.9417822**. It better than the Naive Mean-Baseline Model but it is also much higher than the target RMSE (below 0.87) and that indicates poor performance for the model.

3.3 Movie + User Model, a User-based approach

The second Non-Naive Model considers that each user has different preference of movies and rate differently according to their perspectives.

The formula used is:

Yu,i = ˆ*µ* + *bi* + *bu* + _*u,i*

With ˆ*µ* is the mean and *"i,u* is the independent errors sampled from the same distribution centered at 0. The *bi* is a measure for the popularity of movie *i*, i.e. the bias of movie *i*. The *bu* is a measure for the mildness of user *u*, i.e. the bias of user *u*.

The RMSE on the validation dataset is 0.8639665 which is very good. The Movie+User Based Model has obtained the required performance but by applying regularization, the model can be improved by some amount.

4 Results

This is the summary results for all the model built, trained on edx dataset and validated on the validation dataset.

rmse_results

	model	RMSE
1	Naive Mean-Baseline Model	1.0526979
2	Movie-Based Model	0.9417822
3	Movie+User Based Model	0.8639665

5 Conclusion

After training different models, it’s very clear that movieId and userId are the main contributors for prediction. Without regularization, the model has achieved the desired performance, but by applying regularization and adding the genre predictor, performance can be improved and RMSE can be reduced.

6 Appendix

```
##Installing required packages
install.packages("forcats")
install.packages("kableExtra")

#Loading the libraries for the project
library(ggplot2)
library(kableExtra)
library(stringr)
library(tidyr)
library(tibble)
library(tidyverse)
library(dslabs)
library(dbplyr)
library(caret)
library(broom)
library(naivebayes)
library(pdftools)
library(rvest)
library(timeDate)
library(readr)
library(purrr)
library(lubridate)
library(labeling)
library(dplyr)
library(e1071)
library(data.table)

# Create edx set, validation set, and final file

dl <- tempfile()
download.file("http://files.grouplens.org/datasets/movielens/ml-10m.zip", dl)
```

```
ratings <- fread(text = gsub("::", "\t", readLines(unzip(dl, "ml-10M100K/ratings.dat"))),
                 col.names = c("userId", "movieId", "rating", "timestamp"))

movies <- str_split_fixed(readLines(unzip(dl, "ml-10M100K/movies.dat")), "\\::", 3)
colnames(movies) <- c("movieId", "title", "genres")
movies <- as.data.frame(movies) %>% mutate(movieId = as.numeric(levels(movieId))[movieId],
                                           title = as.character(title),
                                           genres = as.character(genres))

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

# Validation set will be 10% of MovieLens data
set.seed(1, sample.kind="Rounding")
# if using R 3.5 or earlier, use `set.seed(1)` instead
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, list = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]

# Make sure userId and movieId in validation set are also in edx set
validation <- temp %>%
  semi_join(edx, by = "movieId") %>%
  semi_join(edx, by = "userId")

# Add rows removed from validation set back into edx set
removed <- anti_join(temp, validation)
edx <- rbind(edx, removed)

rm(dl, ratings, movies, test_index, temp, movielens, removed)

# Exploratory Data Analysis

## Inital data Exploration

#The 10 Millions dataset is divided into two dataset: "edx" for training purpose and "validation" for the validation phase.


#**edx dataset**
#Defining the root mean square error function
```

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

#Viewing fisrt 6 rows of edx and validation dataframes
head(edx)
head(validation)

#Finding the number of unique users and movies in the edx dataframe
edx %>% summarize(Users = n_distinct(userId), Movies = n_distinct(movieId))

#***********Dataset Pre-Processing and Feature Engineering************************


# Convert timestamp to a human readable date



#Adding a date column to both frames with time zone as Greenwich Mean Time
validation$date <- as.POSIXct(validation$timestamp, origin='1970-01-01',tz="GMT")
edx$date <- as.POSIXct(edx$timestamp,origin='1970-01-01',tz="GMT")

#Viewing first 6 rows of edx and validation dataframes
head(validation)
head(edx)

#Adding month and year columns to both dataframes
validation$month_rated <- format(validation$date,"%m")
validation$year_rated <- format(validation$date,"%y")
edx$year_rated <- format(edx$date,"%y")
edx$month_rated <- format(edx$date,"%m")

#validation <- validation %>% mutate(title = str_squish(title)) %>% extract(title,c("titleTemp",
"release"),regex = "^(.*) \\(([0-9 \\-]*)\\)$",remove = F) %>%mutate(release =
if_else(str_length(release) > 4,as.integer(str_split(release, "-",simplify =
T)[1]),as.integer(release)))

#Adding release date column to validation
validation <- validation %>%mutate(title = str_trim(title)) %>%extract(title, c("titleTemp",
"release"),regex = "^(.*) \\(([0-9 \\-]*)\\)$",remove = F) %>%mutate(release =
if_else(str_length(release) > 4,as.numeric(str_split(release, "-",simplify =
T)[1]),as.numeric(release))) %>%mutate(title = if_else(is.na(titleTemp),title,titleTemp))
```

```
validation<-validation %>% select(-titleTemp)

#Viewing first 6 rows of edx and validation data frames
head(validation)
head(edx)

#Adding release date column to edx
edx <- edx %>% mutate(title = str_squish(title)) %>% extract(title,c("titleTemp",
"release"),regex = "^(.*) \\(([0-9 \\-]*)\\)$",remove = F) %>%mutate(release =
if_else(str_length(release) > 4,as.integer(str_split(release, "-",simplify =
T)[1]),as.integer(release)))
edx<-edx %>% select(-titleTemp)
head(edx)

# Extract the genre in validation datasets
validation <- validation %>%mutate(genre = fct_explicit_na(genres,na_level = "(no genres
listed)")) %>%separate_rows(genre, sep = "\\|")

# Extract the genre in edx datasets
edx <- edx %>% mutate(genre = fct_explicit_na(genres,na_level = "(no genres listed)")) %>%
separate_rows(genre,sep = "\\|")

#Viewing fisrt 6 rows of edx and validation dataframes
head(edx)
head(validation)

#Removing the unnecessary columns in both data frames
validation <- validation %>% select(-genres,-timestamp,-date)
edx <- edx %>% select(-genres,-timestamp,-date)

# Convert the columns into the desired data type

validation$month_rated <- as.numeric(validation$month_rated)

validation$year_rated <- as.numeric(validation$year_rated)

edx$year_rated <- as.numeric(edx$year_rated)

edx$month_rated <- as.numeric(edx$month_rated)
```

```
#******************Processed edx datadaset****************************

head(edx)

#******************Processed validation datadaset***************************

head(validation)

#**************END OF DATA PROCESSING************************************

#*******MOVIE AND RATING HISTOGRAMS************************************


#movies released per year
hist(edx$release)

#rating distribution
hist(edx$rating, main="Distribution of User's Ratings", xlab="Rating")

#********RATING FREQUENCY DISTRIBUTION HISTOGRAMS*****

### Numbers of Ratings per Movie

ggplot(edx, aes(movieId)) + theme_grey()  + geom_histogram(bins=700) + labs(title = "Ratings
Frequency Distribution Per Title (MovieID)",x = "Title (MovieID)",y = "Frequency")


#Number of ratings per user id

ggplot(edx, aes(userId)) +theme_grey()  +geom_histogram(bins=200) +labs(title = "Ratings
Frequency Distribution Per Title (MovieID)",x = "Title (MovieID)",y = "Frequency")

#*********************RATING FREQUENCY DISTRIBUTION PLOTS***********
#Rating frequency distribution

ggplot(edx, aes(rating)) + theme_grey()  + geom_histogram() +labs(title = "Ratings Frequency
Distribution ", x = "Rating", y = "Frequency")
```

```
#Ratings Frequency Distribution Per Title - TOP 20 Movies

edx %>% group_by(title) %>% summarise(count = n()) %>% arrange(desc(count))
%>%head(n=20) %>% ggplot(aes(title, count)) +theme_gray()  +geom_col() +theme(axis.text.x
= element_text(angle = 90, hjust = 1, size = 7)) +labs(title = "Ratings Frequency Distribution Per
Title - TOP 20 Movies",x = "Title",y = "Frequency")

#Ratings Frequency Distribution Per Year - TOP 10

edx %>% group_by(release) %>% summarise(count = n()) %>% arrange(desc(count))
%>%head(n=10) %>%ggplot(aes(release, count)) +theme_gray() +geom_col()
+theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 6)) +labs(title = "Ratings
Frequency Distribution Per Year - TOP 10",x = "Title", y = "Frequency")

#Ratings Frequency Distribution Per genre - TOP 15

edx %>% group_by(genre) %>% summarise(count = n()) %>% arrange(desc(count)) %>%
head(n=15) %>% ggplot(aes(genre, count)) + theme_gray()  + geom_col() +
theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 6)) +
labs(title = "Ratings Frequency Distribution Per genre - TOP 15", x = "Title", y = "Frequency")
head(edx)

#**************RATING FREQUENCY DISTRIBUTION TABLES*******************
#Rating frequency distribution per title

edx %>% group_by(title) %>% summarise(count = n()) %>% arrange(desc(count)) %>%
head(n=25)

#Rating frequency distribution per release year

edx %>% group_by(release) %>% summarise(count = n()) %>% arrange(desc(count)) %>%
head(n=25)
```

```
#*****************MEDIAN DISTRIBUTION HISTOGRAMS*******************
### Median Distribution per Title (Movie) histogram
edx %>%
  group_by(title) %>%
  summarise(median = median(rating)) %>%
  ggplot(aes(median)) +
  theme_gray()  +
  geom_histogram(bins=12) +
  labs(title = "Median Distribution per Title",x = "Median",y = "Frequency")

### Median distribution per release (year) histogram

edx %>%
  group_by(release) %>%
  summarise(median = median(rating)) %>%
  ggplot(aes(median)) +
  theme_gray()  +
  geom_histogram(bins=12) +
  labs(title = "Median Distribution per Release",x = "Median",y = "Frequency")

### Median distribution per user histogram

edx %>%
  group_by(userId) %>%
  summarise(median = median(rating)) %>%
  ggplot(aes(median)) +
  theme_gray()  +
  geom_histogram(bins=12) +
  labs(title = "Median Distribution per user",x = "Median",y = "Frequency")
```

```
#*************************MEDIAN DISTRIBUTION TABLES*******************

### Median distribution per title(movie) table

edx %>%
  group_by(title) %>%
  summarise(median = median(rating)) %>%
  arrange(desc(median)) %>%
  head(n=25)

### Median distribution per release year table

edx %>%
  group_by(release) %>%
  summarise(median = median(rating)) %>%
  arrange(desc(median)) %>%
  head(n=25)

### Median distribution per user table

edx %>%
  group_by(userId) %>%
  summarise(median = median(rating)) %>%
  arrange(desc(median)) %>%
  head(n=25)

#*************************MEAN DISTRIBUTION HISTOGRAMS*****************

###Mean distribution per title histogram

edx %>%
  group_by(title) %>%
  summarise(mean = mean(rating)) %>%
  ggplot(aes(mean)) +
  theme_light()  +
  geom_histogram(bins=12) +
  labs(title = "Mean Distribution per Title",x = "Mean",y = "Frequency")
```

```
###Mean distribution per release histogram

edx %>%
  group_by(release) %>%
  summarise(mean = mean(rating)) %>%
  ggplot(aes(mean)) +
  theme_bw()  +
  geom_histogram(bins=12) +
  labs(title = "Mean Distribution per release",x = "Mean", y = "Frequency")


###Mean distribution per user histogram

edx %>%
  group_by(userId) %>%
  summarise(mean = mean(rating)) %>%
  ggplot(aes(mean)) +
  theme_bw()  +
  geom_histogram(bins=12) +
  labs(title = "Mean Distribution per user",x = "Mean",y = "Frequency")


#************************MEAN DISTRIBUTION TABLES**********************

##MEAN DISTRIBUTION PER TITLE TABLE

edx %>%
  group_by(title) %>%
  summarise(mean = mean(rating)) %>%
  arrange(desc(mean)) %>%
  head(n=10)

##MEAN DISTRIBUTION PER RELEASE YEAR TABLE

edx %>%
  group_by(release) %>%
  summarise(mean = mean(rating)) %>%
  arrange(desc(mean)) %>%
  head(n=10)
```

```
##MEAN DISTRIBUTION PER USER TABLE
edx %>%
  group_by(userId) %>%
  summarise(mean = mean(rating)) %>%
  arrange(desc(mean)) %>%
  head(n=10)




##*****************************Rating distributions****************************

### Rating Distribution per Genre

#**Overview of Rating distribution over Genre**

edx %>%
  group_by(genre) %>%
  summarise(count = n()) %>%
  ggplot(aes(genre, count)) +
  theme_gray()  +
  geom_col() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Ratings Frequency Distribution Per Genre",x = "Genre",y = "Frequency")

#**Overview of Rating distribution over months**

edx %>%
  group_by(month_rated) %>%
  summarise(count = n()) %>%
  ggplot(aes(month_rated, count)) +
  theme_gray()  +
  geom_col() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Ratings Frequency Distribution Per month",x = "month",y = "Frequency")
```

```
#**************************RATING FREQUENCY TABLES*******************

#rating per genre

edx %>%
  group_by(genre) %>%
  summarise(count = n()) %>%
  arrange(desc(count))

#rating per month

edx %>%
  group_by(month_rated) %>%
  summarise(count = n()) %>%
  arrange(desc(count))

#*********************Rating distribution plots**********************************
### Mean Distribution per Genre

edx %>%
  group_by(genre) %>%
  summarise(mean = mean(rating)) %>%
  ggplot(aes(genre, mean)) +
  theme_bw()  +
  geom_col() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Mean Distribution per Genre",x = "Genre",y = "Mean")

### Median Distribution per Genre

edx %>%
  group_by(genre) %>%
  summarise(median = median(rating)) %>%
  ggplot(aes(genre, median)) +
  theme_grey()  +
  geom_col() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Median Distribution per Genre",x = "Genre",y = "Median")
```

```
### Mode Distribution per Genre
edx %>%
  group_by(genre) %>%
  summarise(mode = mode(rating)) %>%
  ggplot(aes(genre, mode)) +
  theme_gray()  +
  geom_col() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Mode Distribution per Genre",x = "Genre",y = "Mode")

#*************Distribution tables*********************************


####median distribution per genre

edx %>%

  group_by(genre) %>%
  summarise(median = median(rating)) %>%
  arrange(desc(median)) %>%
  head(n=10)

###mean distribution per genre

edx %>%
  group_by(genre) %>%
  summarise(mean = mean(rating)) %>%
  arrange(desc(mean)) %>%
  head(n=10)

#************* Analysis - Model Building and Evaluation********************

## Naive Baseline Model
mean(edx$rating)

### Naive Mean-Baseline Model

# Calculate the average of all movies
mu_hat <- mean(edx$rating)
mu_hat
```

```
# Predict the RMSE on the validation set
rmse_mean_result <- RMSE(validation$rating, mu_hat)
rmse_mean_result

# Creating a results dataframe that contains all RMSE results
rmse_results <- data.frame(model="Naive Mean-Baseline Model", RMSE=rmse_mean_result)
rmse_results

## Movie-Based Model, a Content-based Approach
# Calculate the average per each movie

movie_rmse <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu_hat))
movie_rmse

# Predict the ratings for validation dataset

rmse_validation <- validation %>%
  left_join(movie_rmse, by='movieId') %>%
  mutate(pred = mu_hat + b_i) %>%
  pull(pred)
rmse_validation

rmse_validation_result <- RMSE(validation$rating, rmse_validation)
rmse_validation_result

# Adding the results to the results dataset
rmse_results <- rmse_results %>% add_row(model="Movie-Based Model",
RMSE=rmse_validation_result)
rmse_results

#The RMSE on the ```validation``` dataset is **0.9417822**. It is slightly better than the Naive
Mean-Baseline Model, but it is also far from the required RMSE (below 0.87) leading to poor
performance for the model.
```

```
## Movie + User Model, a User-based approach


# Calculate the average by movie
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - mu_hat))


# Calculate the average for every user
user_avgs <- edx %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u = mean(rating - mu_hat - b_i))

# Compute the predicted ratings on validation dataset

rmse_movie_plus_user_model <- validation %>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  mutate(pred = mu_hat + b_i + b_u) %>%
  pull(pred)

rmse_movie_plus_user_model_result<-RMSE(validation$rating, rmse_movie_plus_user_model)

# Adding the results to the results dataset
rmse_results <- rmse_results %>% add_row(model="Movie+User Based Model",
RMSE=rmse_movie_plus_user_model_result)

rmse_results

#The movie plus user based model has achieved the
#required resultant RMSE of 0.863 which is less than 0.8649
#The model can be improved by using regularisation technique.
```