

BUILDING A MOVIE RECOMMENDATION SYSTEM USING THE MOVIELENS RESEARCH DATA

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1. INTRODUCTION

In this project, we create a movie recommendation system using the MovieLens dataset. You can obtain the GroupLens Research data from [this link](#). Our main aim is to perform a data analysis and through visualization, find patterns to assist us in building a model that will provide an optimum movie recommendation to users.

The dataset is composed of 10000054 observations with:

- 69878 unique users and
- 10677 movies

The key steps performed include:

- Preparation of the work environment.
- Preparation, exploration and visualizations of the data
- Analysis of the observations.
- Calculation of the optimal RMSE based on movieId and userId.

On following the above steps, our data model will reveal that the best predictors used to provide the optimum recommendation system are moveId and UserId. The RMSE is **0.8431355**.

2. METHODS AND ANALYSIS

2.1 Work Environment Preparation

We are going to use the following libraries:

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

Next we shall download the data

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

2.2 Data Wrangling

We build the desired dataset which we shall use to build our model using the code below:

```
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)
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, list = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]

validation <- temp %>% semi_join(edx, by = "movieId") %>% semi_join(edx, by = "userId")

removed <- anti_join(temp, validation)
edx <- rbind(edx, removed)
```

```
#Add a year column generated from the timestamp column
dates <- as.Date(as.POSIXct(edx$timestamp, origin="1970-01-01"))
edx <- edx %>% mutate(year=year(dates), month=month(dates))
```

We shall use the edx dataset we just created onwards

2.3 Data Exploration and Visualizations

The edx dataset consists of:

Total number of ratings

```
length(edx$rating)
```

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

Total number of movies

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

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

Total number of users

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

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

And we can confirm that each user rated a movie using the following code

```
edx %>% filter(is.na(.ratings))
```

The top 20 most viewed genres are

	genres	count
## 1	Drama	733296
## 2	Comedy	700889
## 3	Comedy Romance	365468
## 4	Comedy Drama	323637
## 5	Comedy Drama Romance	261425
## 6	Drama Romance	259355
## 7	Action Adventure Sci-Fi	219938
## 8	Action Adventure Thriller	149091

```

## 9          Drama|Thriller 145373
## 10         Crime|Drama 137387
## 11         Drama|War 111029
## 12         Crime|Drama|Thriller 106101
## 13 Action|Adventure|Sci-Fi|Thriller 105144
## 14         Action|Crime|Thriller 102259
## 15         Action|Drama|War 99183
## 16         Action|Thriller 96535
## 17         Action|Sci-Fi|Thriller 95280
## 18         Thriller 94662
## 19         Horror|Thriller 75000
## 20         Comedy|Crime 73286

```

While the top 20 best rated movies are

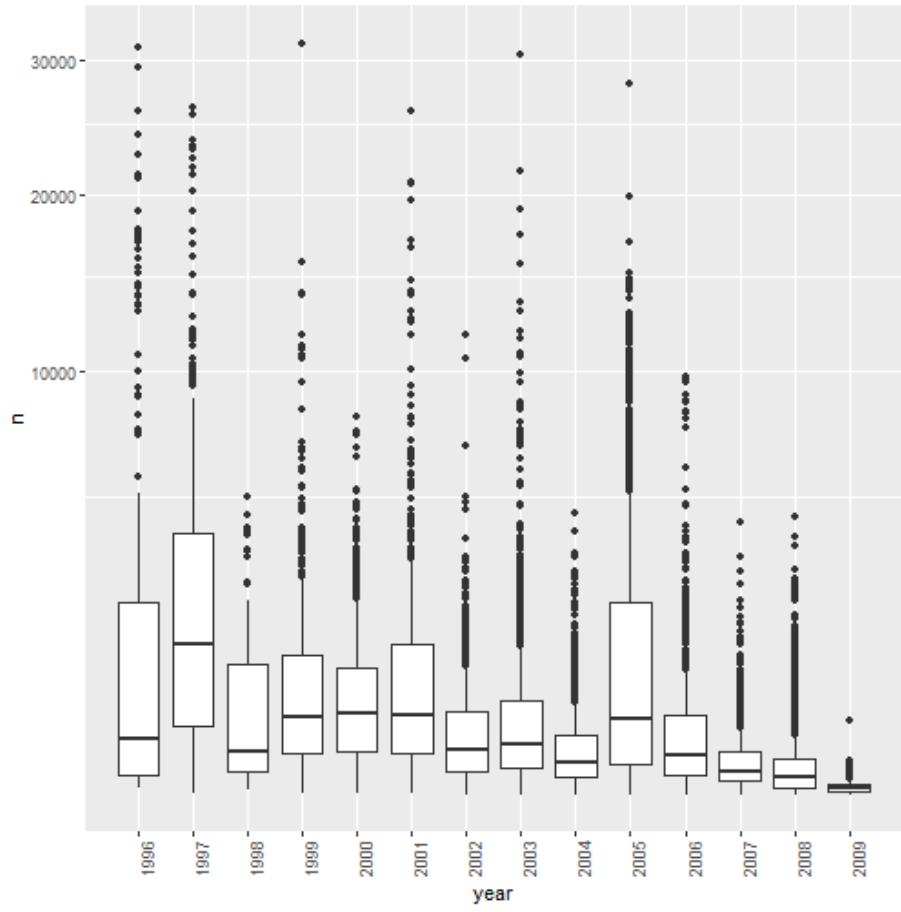
	movieId	title
## 1	296	Pulp Fiction (1994)
## 2	356	Forrest Gump (1994)
## 3	593	Silence of the Lambs, The (1991)
## 4	480	Jurassic Park (1993)
## 5	318	Shawshank Redemption, The (1994)
## 6	110	Braveheart (1995)
## 7	457	Fugitive, The (1993)
## 8	589	Terminator 2: Judgment Day (1991)
## 9	260	Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977)
## 10	150	Apollo 13 (1995)
## 11	592	Batman (1989)
## 12	1	Toy Story (1995)
## 13	780	Independence Day (a.k.a. ID4) (1996)
## 14	590	Dances with Wolves (1990)
## 15	527	Schindler's List (1993)
## 16	380	True Lies (1994)
## 17	1210	Star Wars: Episode VI - Return of the Jedi (1983)
## 18	32	12 Monkeys (Twelve Monkeys) (1995)
## 19	50	Usual Suspects, The (1995)
## 20	608	Fargo (1996)
##	count	
## 1	31362	
## 2	31079	
## 3	30382	
## 4	29360	
## 5	28015	
## 6	26212	
## 7	25998	
## 8	25984	

```

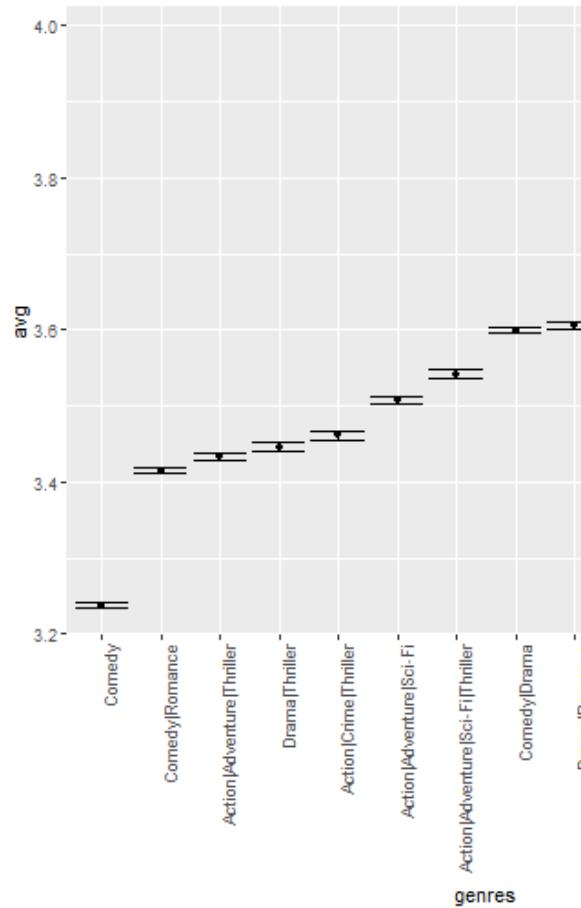
## 9 25672
## 10 24284
## 11 24277
## 12 23790
## 13 23449
## 14 23367
## 15 23193
## 16 22823
## 17 22584
## 18 21891
## 19 21648
## 20 21395

```

From the figure below, we can conclude that **1997** had the highest accumulated



ratings overall,

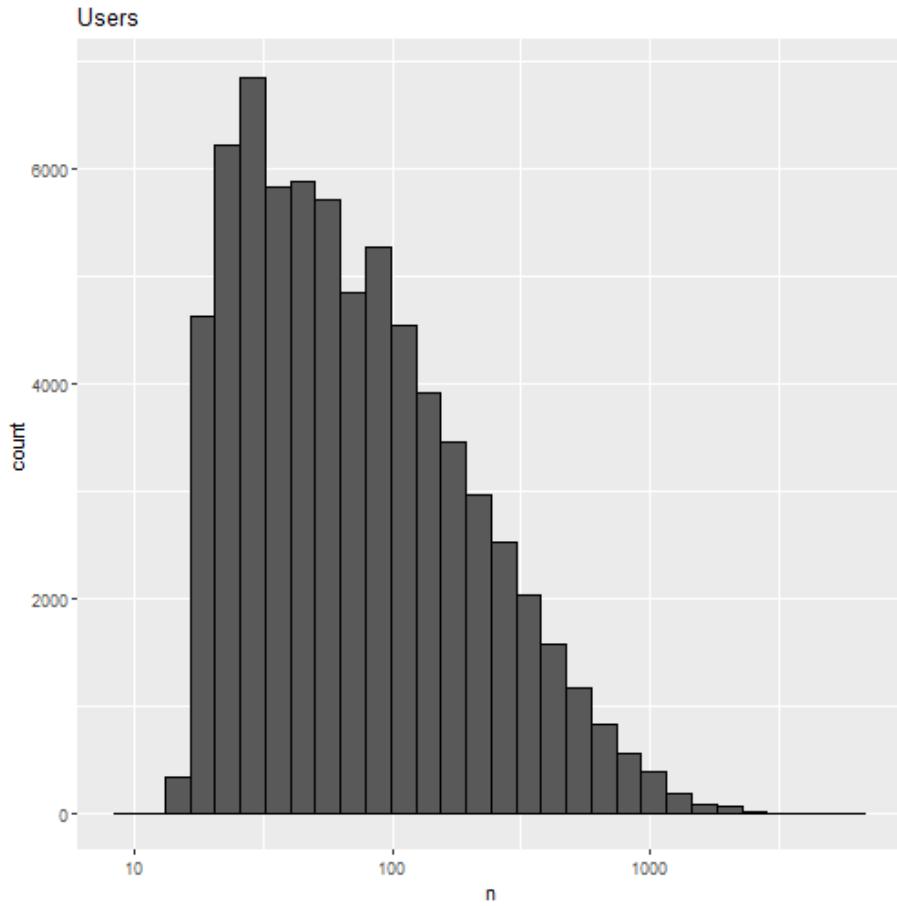


And the genre **Drama/War** with the highest overall ratings.

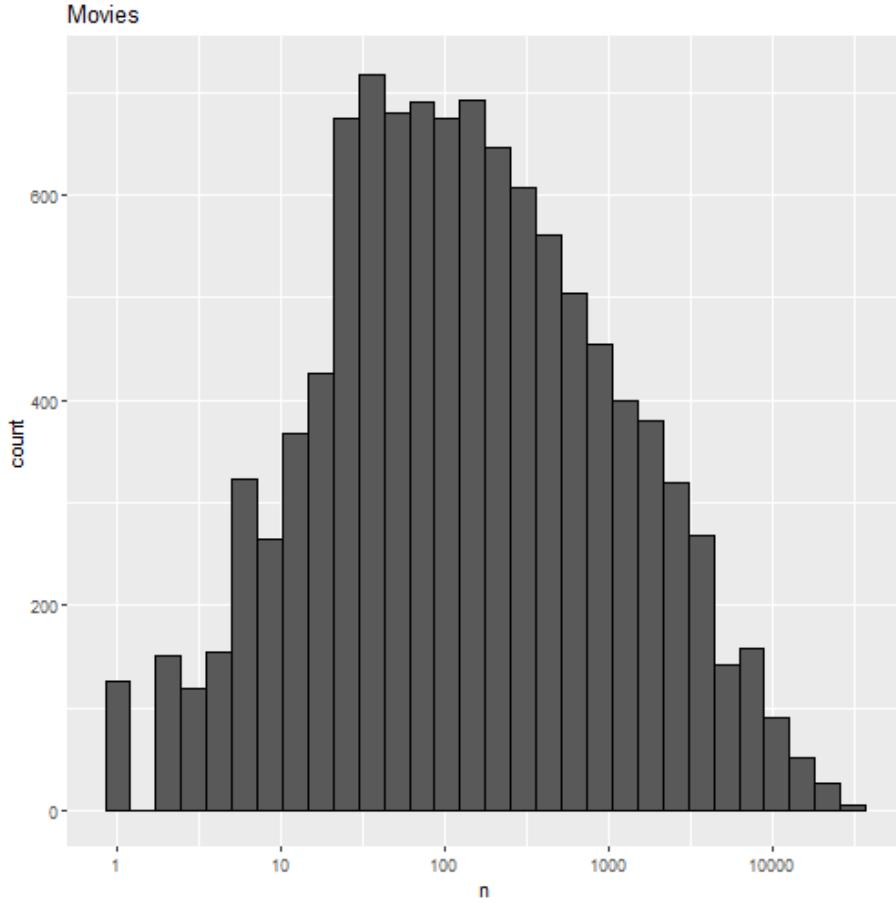
2.4 Data Analysis and Modelling

Let's look at some of the general properties of the data to better understand the challenge.

The first observation is that some users are more active than others at rating movies. Notice that some users have rated over 1,000 movies while others have only rated a handful.



The second thing we notice is that some movies get rated more than others. Here is the distribution.



From the two observations above, we can then prove that there's indeed a movie variability and a user variability. We'll use two predicts to model the data.

To compare different models or to see how well we're doing compared to some baseline, we need to quantify what it means to do well. We need a loss function, in this case the residual mean squared error since we can interpret it as similar to standard deviation. It is the typical error we make when predicting a movie rating. This will therefore be our modelling approach.

We're going to predict the same rating for all movies, regardless of the user and movie. In this case, that's just the average of all the ratings. Using that, we'll get the first RMSE.

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

mu_hat <- mean(train_set$rating)
naive_rmse <- RMSE(test_set$rating, mu_hat)
```

```
naive_rmse  
  
## [1] 1.059904
```

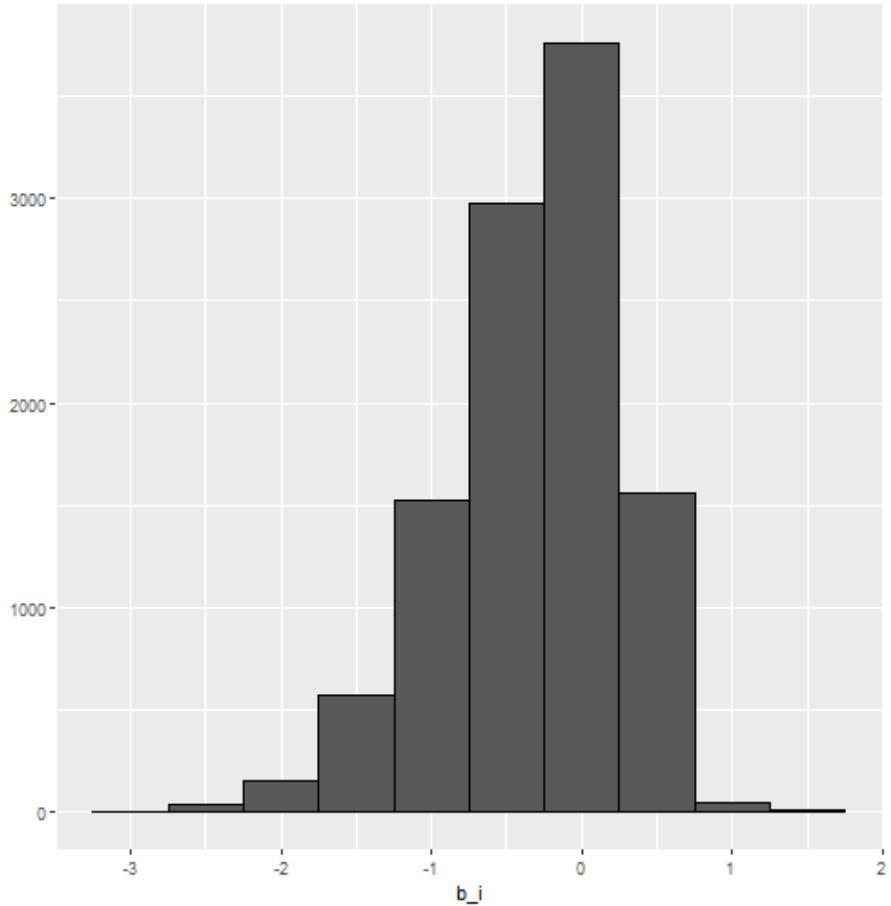
Because as we go along we will be comparing different approaches, we're going to create a table that's going to store the results that we obtain as we go along.

```
rmse_results <- data_frame(method = "Just the average", RMSE = naive_rmse)  
  
## Warning: `data_frame()` is deprecated, use `tibble()`.  
## This warning is displayed once per session.
```

2.5 LAMBDA and RMSE Calculations

Now let's see how much our prediction improves once we predict using the model that we just fit.

```
mu <- mean(train_set$rating)  
  
movie_avgs <- train_set %>% group_by(movieId) %>% summarize(b_i = mean(rating - mu))  
  
movie_avgs %>% qplot(b_i, geom ="histogram", bins = 10, data = ., color = I("black"))
```



```

predicted_ratings <- mu + test_set %>% left_join(movie_avgs, by='movieId') %>% .\$b_i

model_1_rmse <- RMSE(predicted_ratings, test_set$rating)

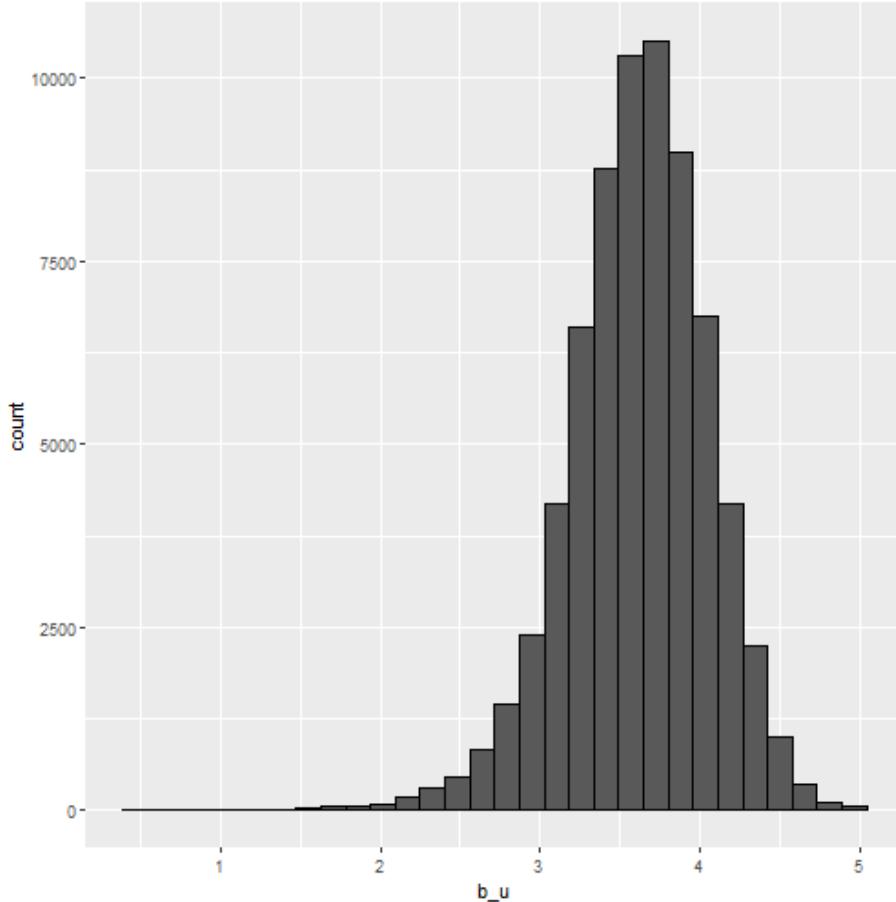
rmse_results <- bind_rows(rmse_results, data_frame(method="Movie Effect Model", RMSE = model_1_rmse))

```

Our residual mean squared error did drop a little bit. From **1.0599043** to **0.9437429**

method	RMSE
Just the average	1.0599043
Movie Effect Model	0.9437429

We continue to make it better. This time we factor in user variability. Are different users different in terms of how they rate movies? To explore the data, let's compute the average rating for user, u , for those that have rated over 100 movies.



Note that there is substantial variability across users, as well. Some users are very cranky. And others love every movie they watch, while others are somewhere in the middle. Now we move ahead and implement user variability.

```
user_avgs <- test_set %>% left_join(movie_avgs, by='movieId') %>% group_by(userId) %>%
  summarize(b_u = mean(rating - mu - b_i))

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

model_2_rmse <- RMSE(predicted_ratings, test_set$rating)
```

```
rmse_results <- bind_rows(rmse_results,data_frame(method="Movie + User Effects Model", RMSE))
```

3. RESULT

We see that now we obtain a further improvement. Our residual mean squared error dropped down to about **0.84**, hence this is our optimal model.

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

method	RMSE
Just the average	1.0599043
Movie Effect Model	0.9437429
Movie + User Effects Model	0.8431355

4. CONCLUSION

The spirit of the project was to predict movie ratings from a long list of rated movies. Where an optimal RMSE of 0.8431355 is achieved. Throughout the analysis we have discovered patterns and trends beyond the project's own objective.