HarvardX PH125.9x Data Science: MovieLens Capstone Project

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Contents

Introduction

In today’s era of streaming platforms like Netflix, Amazon Prime, and Disney+, personalized content recommendations have become essential for engaging users and improving their experience. This project, part of the HarvardX Data Science Capstone (PH125.9x), aims to develop a movie recommendation system using the **MovieLens 10M dataset**. The dataset includes over **10 million ratings** from nearly **70,000 users** for more than **10,000 movies**.

The goal is to predict user ratings for movies they have not yet watched, leveraging collaborative filtering techniques and achieving a **Root Mean Square Error (RMSE)** of less than **0.8649**.

Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a widely used metric for evaluating the accuracy of regression models, including recommendation systems. It measures the average difference between predicted and actual ratings, quantifying how well a model’s predictions align with the true values. Mathematically, RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{u,i}(\hat{y}_{u,i} - y_{u,i})^2}$$

where:

- *N* is the total number of observations.
- ŷ is the predicted rating.
- y is the actual rating.

A lower RMSE indicates better predictive accuracy, meaning the model's predictions are closer to the true ratings. For this project, we aim to optimize the model to achieve an RMSE below **0.8649**, ensuring precise and reliable movie recommendations.

Methods and Analysis

First, the project begins by preparing and loading the dataset from the GroupLens website. The data is preprocessed and any NAs will be removed to ensure the data is clean. The data is initially split into two datasets: “edx” (used for model training and development) and “validation” (used solely for evaluating the final model's performance). The edx dataset is further divided into training and test sets to build and fine-tune the recommendation model.

Data Preparation and Required Packages

```
#Install and Load Required 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")

library(tidyverse)
library(caret)

# Download the MovieLens 10M dataset:
# https://grouplens.org/datasets/movielens/10m/
# http://files.grouplens.org/datasets/movielens/ml-10m.zip
options(timeout = 120)

dl <- "ml-10M100K.zip"
if(!file.exists(dl))
  download.file("https://files.grouplens.org/datasets/movielens/ml-10m.zip", dl)

#Unzip and Load the Data
ratings_file <- "ml-10M100K/ratings.dat"
if(!file.exists(ratings_file))
  unzip(dl, ratings_file)

movies_file <- "ml-10M100K/movies.dat"
if(!file.exists(movies_file))
  unzip(dl, movies_file)

#Read and Process the Ratings Data
ratings <- as.data.frame(str_split(read_lines(ratings_file), fixed("::"), simplify = TRUE),
                         stringsAsFactors = FALSE)
```

```
colnames(ratings) <- c("userId", "movieId", "rating", "timestamp")
ratings <- ratings %>%
  mutate(userId = as.integer(userId),
         movieId = as.integer(movieId),
         rating = as.numeric(rating),
         timestamp = as.integer(timestamp))

#Read and Process the Movies Data
movies <- as.data.frame(str_split(read_lines(movies_file), fixed("::"), simplify = TRUE),
                        stringsAsFactors = FALSE)
colnames(movies) <- c("movieId", "title", "genres")
movies <- movies %>%
  mutate(movieId = as.integer(movieId))

#Merge Ratings and Movies Data
movielens <- left_join(ratings, movies, by = "movieId")

#Create ‘edx’ and ‘final_holdout_test’ Sets
set.seed(1, sample.kind="Rounding") # if using R 3.6 or later
# set.seed(1) # if using R 3.5 or earlier

#Split the data: 10% for final holdout test, 90% for edx
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 final hold-out test set are also in edx set
final_holdout_test <- temp %>%
  semi_join(edx, by = "movieId") %>%
  semi_join(edx, by = "userId")

# Add rows that were removed from final hold-out test set back into edx set
removed <- anti_join(temp, final_holdout_test)
edx <- rbind(edx, removed)

# Clean up
rm(dl, ratings, movies, test_index, temp, movielens, removed)
```

Description of the Dataset

The MovieLens 10M dataset is a rich source of information that includes:

Name	Format	Description
userId	Numerical	Unique identifier for each user.
MovieId	Numerical	Unique identifier for each movie.
rating	Numerical	Rating given by a user to a movie on a scale from 0.5 to 5.0
timestamp	Numerical	Unix timestamp of when the rating was provided.
title	Character string	Title of the movie, including its release year.
genres	Character string	Genres associated with the movie (e.g., Action, Comedy).

The complete dataset includes **10,677 unique movies** rated by **69,878 users**, resulting in **10 million** records. The dataset is highly sparse, as not every user has rated every movie.

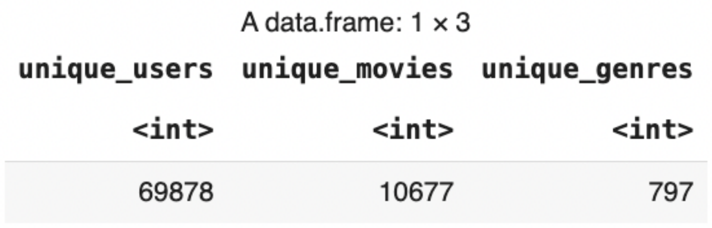
Summary of edx & final_holdout_test

```
# Display Summary of `edx` and `final_holdout_test`
cat("Number of rows in edx:", nrow(edx), "\n")
cat("Number of rows in final_holdout_test:", nrow(final_holdout_test), "\n")
cat("Number of unique users in edx:", length(unique(edx$userId)), "\n")
cat("Number of unique movies in edx:", length(unique(edx$movieId)), "\n")
cat("Number of unique users in final_holdout_test:", length(unique(final_holdout_test$userId)),
"\n")
cat("Number of unique movies in final_holdout_test:",
length(unique(final_holdout_test$movieId)), "\n")

# Preview the edx dataset
glimpse(edx)
```

```
Number of rows in edx: 9000055
Number of rows in final_holdout_test: 999999
Number of unique users in edx: 69878
Number of unique movies in edx: 10677
Number of unique users in final_holdout_test: 68534
Number of unique movies in final_holdout_test: 9809
Rows: 9,000,055
Columns: 6


$ userId    <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, …
$ movieId   <int> 122, 185, 292, 316, 329, 355, 356, 362, 364, 370, 377, 420, …
$ rating    <dbl> 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, …
$ timestamp <int> 838985046, 838983525, 838983421, 838983392, 838983392, 83898…
$ title     <chr> "Boomerang (1992)", "Net, The (1995)", "Outbreak (1995)", "S…
$ genres    <chr> "Comedy|Romance", "Action|Crime|Thriller", "Action|Drama|Sci…
```

Unique Users, Movies, and Genres

```
edx %>% summarize(unique_users = length(unique(userId)),
                  unique_movies = length(unique(movieId)),
                  unique_genres = length(unique(genres)))
```

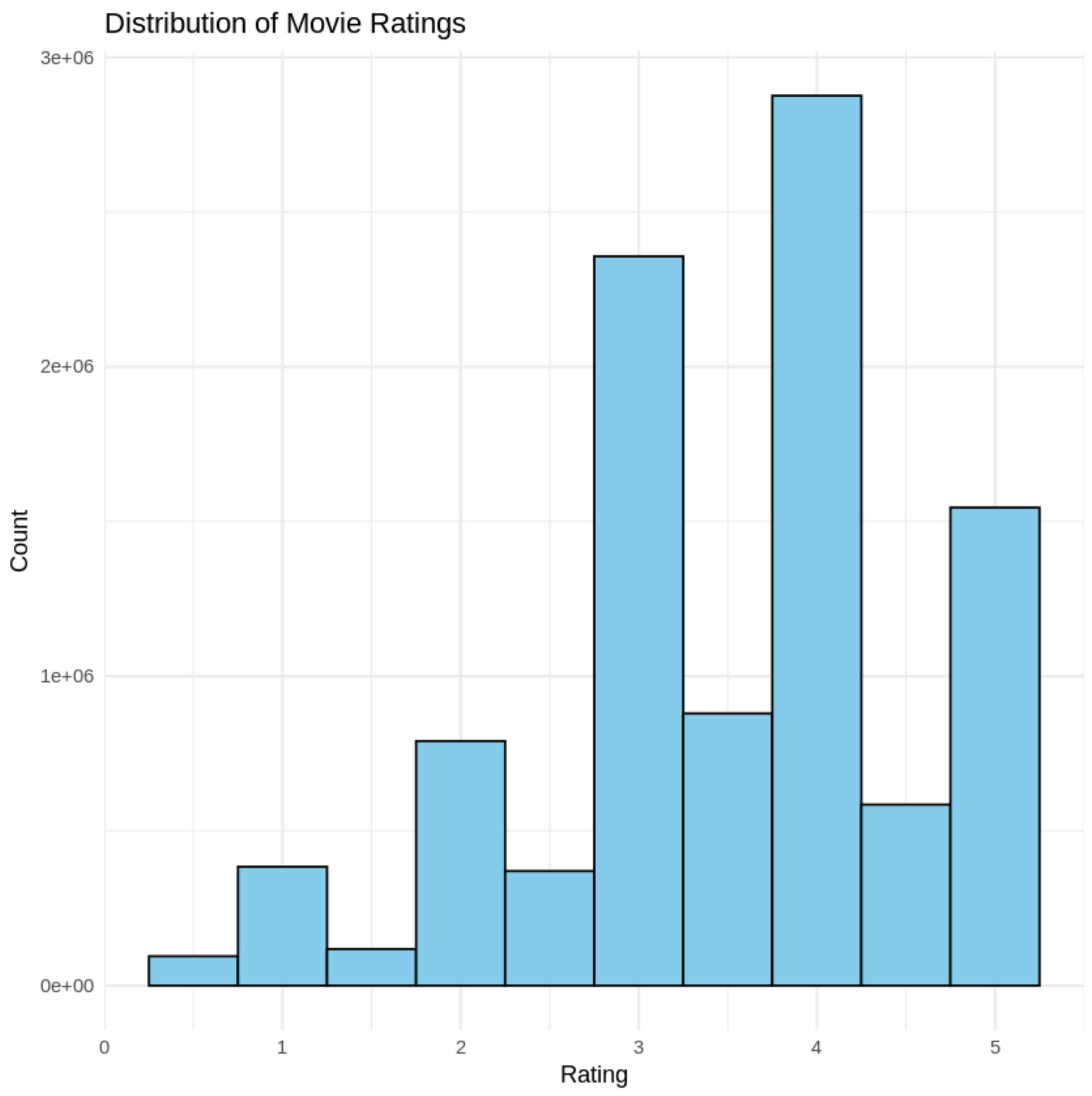


```
                 A data.frame: 1 × 3
unique_users  unique_movies  unique_genres
       <int>          <int>          <int>
       69878          10677            797
```

Visualizing the Distribution of Movie Ratings

Analyzing the distribution of ratings reveals that users tend to give higher ratings, with most ratings clustered between **3.0 and 5.0**. This suggests a positive bias among users, likely driven by selective movie viewing.

```
ratings <- as.data.frame(str_split(read_lines("ml-10M100K/ratings.dat"), fixed("::"), simplify =
TRUE), stringsAsFactors = FALSE)
colnames(ratings) <- c("userId", "movieId", "rating", "timestamp")
ratings <- ratings %>%
  mutate(userId = as.integer(userId),
         movieId = as.integer(movieId),
         rating = as.numeric(rating),
         timestamp = as.integer(timestamp))

# Plot 1: Histogram of Ratings Distribution
ggplot(ratings, aes(x = rating)) +
  geom_histogram(binwidth = 0.5, fill = "skyblue", color = "black") +
  labs(title = "Distribution of Movie Ratings", x = "Rating", y = "Count") +
  theme_minimal()
```



Proportion of Ratings

```
# Calculate the number of ratings greater than or equal to 3
rp <- edx %>% filter(rating >= 3)

# Calculate the proportion of such ratings
proportion <- nrow(rp) / nrow(edx)
cat("Proportion of ratings >= 3:", round(proportion, 4), "\n")
```

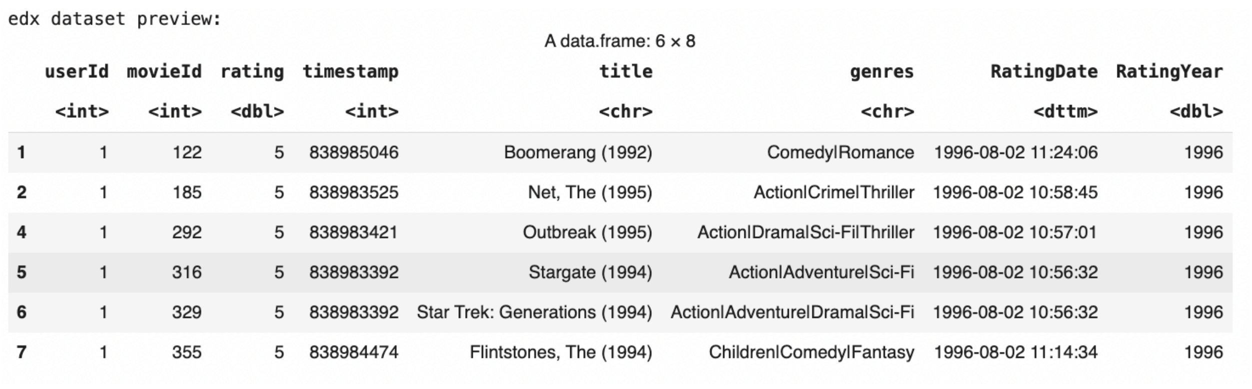
```
```

Proportion of ratings >= 3: 0.8242

Timestamp

The timestamp column was converted to a human-readable format to extract features such as the rating year and rating day of the week.

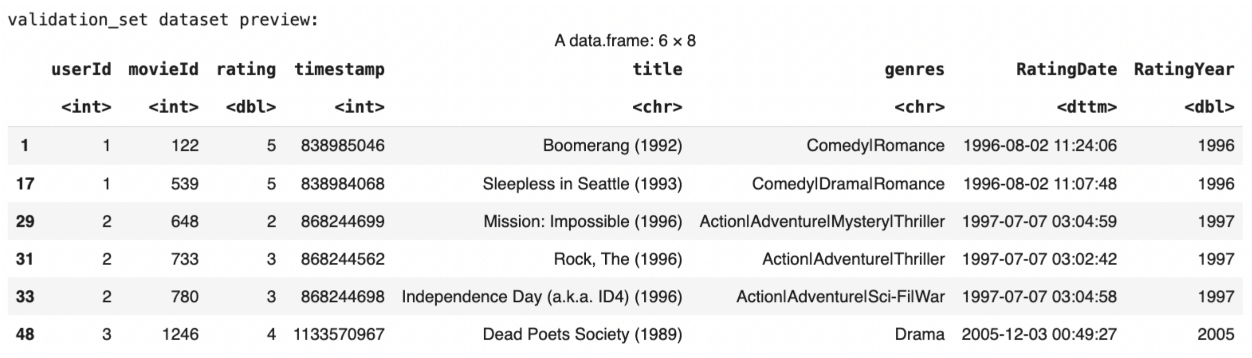
```r
# Load required packages
if (!require(lubridate)) install.packages("lubridate", repos = "http://cran.us.r-project.org")
library(lubridate)

# Convert the timestamp to a readable date format and extract the year
edx <- edx %>%
  mutate(RatingDate = as.POSIXct(timestamp, origin = "1970-01-01"),
         RatingYear = year(RatingDate))

# Convert the timestamp in the validation_set to RatingDate and extract RatingYear
validation_set <- validation_set %>%
  mutate(RatingDate = as.POSIXct(timestamp, origin = "1970-01-01"),
         RatingYear = year(RatingDate))

# Preview the updated edx dataset
cat("edx dataset preview:\n")
head(edx)

# Preview the updated validation_set dataset
cat("\nvalidation_set dataset preview:\n")
head(validation_set)
```



edx dataset preview:

A data.frame: 6 × 8

	userId	movieId	rating	timestamp	title	genres	RatingDate	RatingYear
	<int>	<int>	<dbl>	<int>	<chr>	<chr>	<dttm>	<dbl>
1	1	122	5	838985046	Boomerang (1992)	Comedy|Romance	1996-08-02 11:24:06	1996
2	1	185	5	838983525	Net, The (1995)	Action|Crime|Thriller	1996-08-02 10:58:45	1996
4	1	292	5	838983421	Outbreak (1995)	Action|Drama|Sci-Fi|Thriller	1996-08-02 10:57:01	1996
5	1	316	5	838983392	Stargate (1994)	Action|Adventure|Sci-Fi	1996-08-02 10:56:32	1996
6	1	329	5	838983392	Star Trek: Generations (1994)	Action|Adventure|Drama|Sci-Fi	1996-08-02 10:56:32	1996
7	1	355	5	838984474	Flintstones, The (1994)	Children|Comedy|Fantasy	1996-08-02 11:14:34	1996



validation_set dataset preview:

A data.frame: 6 × 8

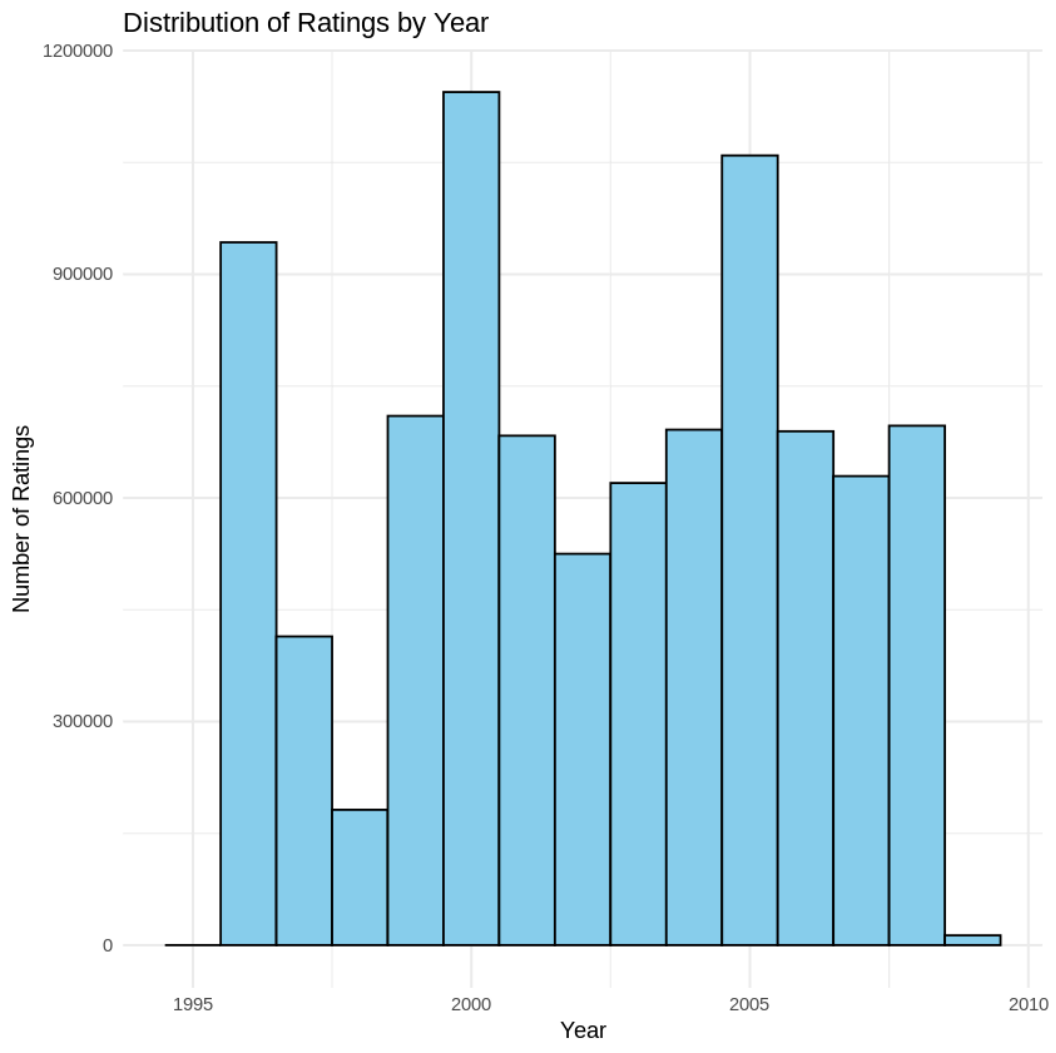
	userId	movieId	rating	timestamp	title	genres	RatingDate	RatingYear
	<int>	<int>	<dbl>	<int>	<chr>	<chr>	<dttm>	<dbl>
1	1	122	5	838985046	Boomerang (1992)	Comedy|Romance	1996-08-02 11:24:06	1996
17	1	539	5	838984068	Sleepless in Seattle (1993)	Comedy|Drama|Romance	1996-08-02 11:07:48	1996
29	2	648	2	868244699	Mission: Impossible (1996)	Action|Adventure|Mystery|Thriller	1997-07-07 03:04:59	1997
31	2	733	3	868244562	Rock, The (1996)	Action|Adventure|Thriller	1997-07-07 03:02:42	1997
33	2	780	3	868244698	Independence Day (a.k.a. ID4) (1996)	Action|Adventure|Sci-Fi|War	1997-07-07 03:04:58	1997
48	3	1246	4	1133570967	Dead Poets Society (1989)	Drama	2005-12-03 00:49:27	2005

RatingYear

```
range(edx$RatingYear)
```

1995 - 2009

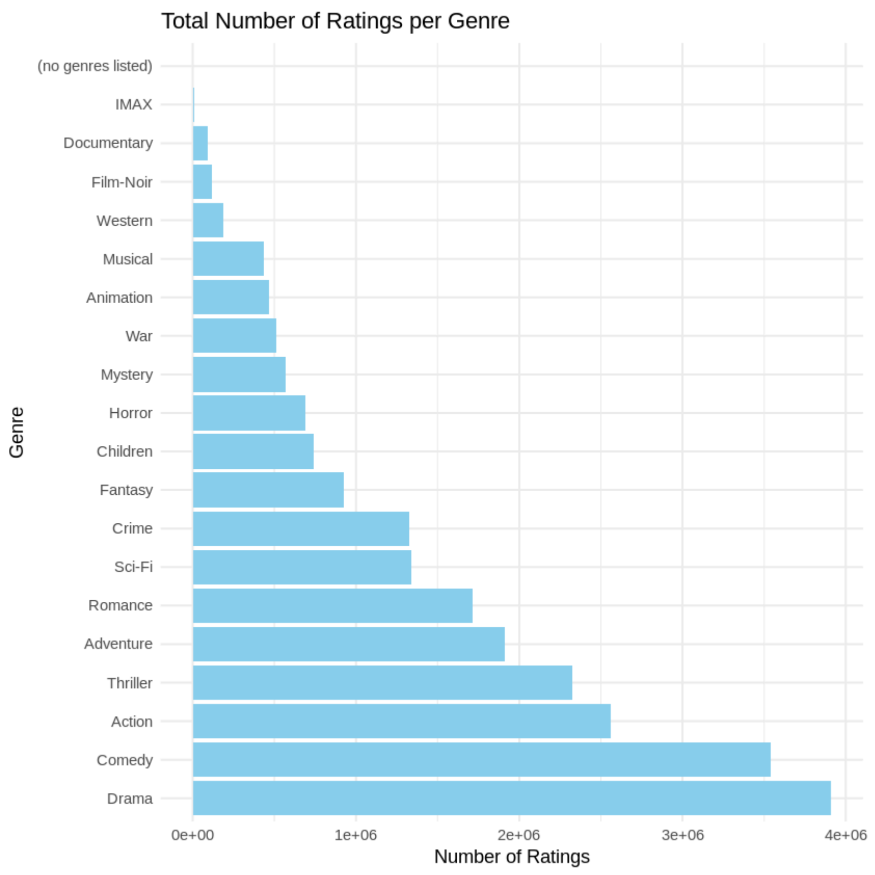
```
edx$RatingYear <-as.numeric(edx$RatingYear)
str(edx)

# Plot the histogram of RatingYear
ggplot(edx, aes(x = RatingYear)) +
  geom_histogram(binwidth = 1, fill = "skyblue", color = "black") +
  labs(title = "Distribution of Ratings by Year", x = "Year", y = "Number of Ratings") +
  theme_minimal()
```



Ratings per Genre

Movies are often associated with multiple genres (e.g., "Action|Adventure|Sci-Fi"). To analyze genres effectively, we separated the genres into individual rows.

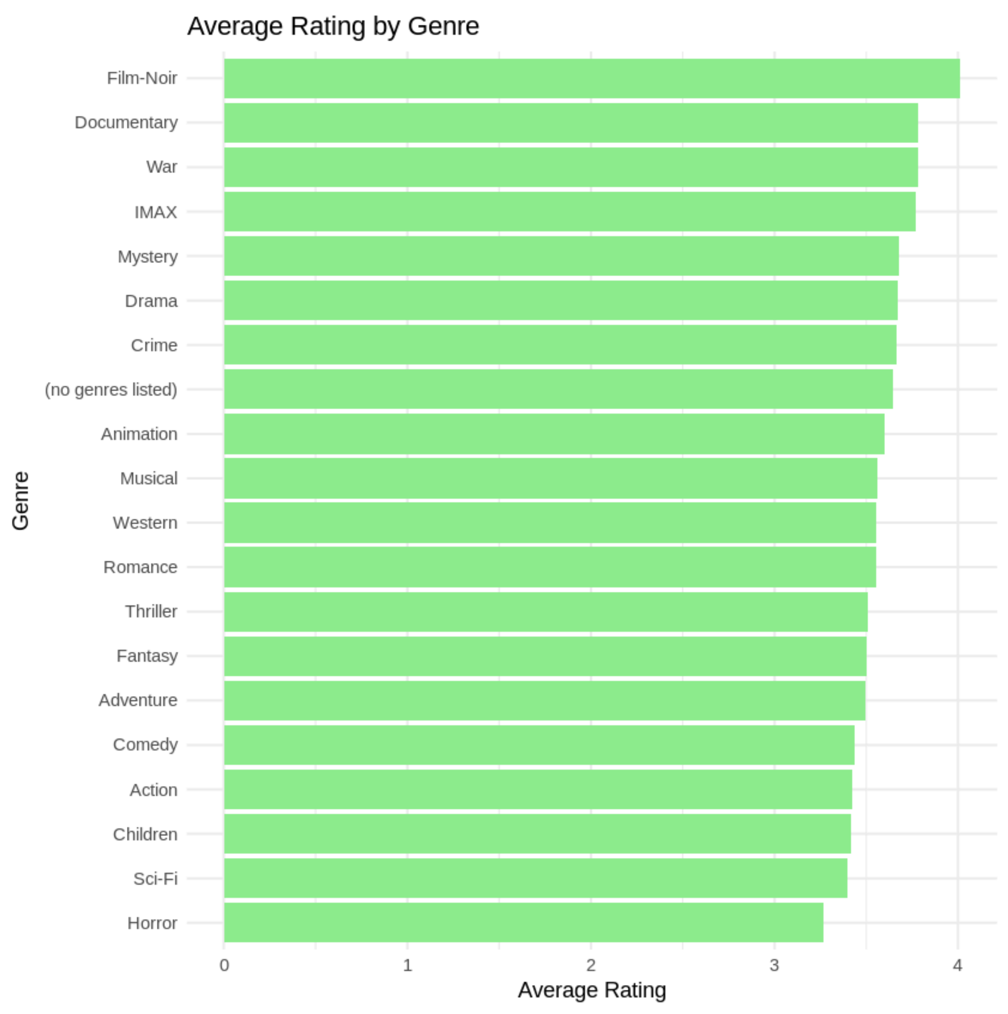
```
# Step 1: Separate rows with multiple genres into individual rows for each genre
edx_genres <- edx %>%
  separate_rows(genres, sep = "\\|")  # Split genres by the '|' delimiter

# Summarize the total number of ratings and average rating for each genre
genre_summary <- edx_genres %>%
  group_by(genres) %>%
  summarize(
    Ratings_Sum = n(),
    Average_Rating = mean(rating, na.rm = TRUE),
    .groups = 'drop'
  ) %>%
  arrange(desc(Ratings_Sum))

# Plot the results using a bar chart
library(ggplot2)
ggplot(genre_summary, aes(x = reorder(genres, -Ratings_Sum), y = Ratings_Sum)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  coord_flip() +
  labs(
    title = "Total Number of Ratings per Genre",
    x = "Genre",
    y = "Number of Ratings"
  ) +
  theme_minimal()
```



Average Rating by Genre

```
# Load required libraries
if (!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
library(tidyverse)

# Calculate Ratings Sum and Average Rating per Genre, then sort by Average Rating
genre_summary <- edx_genres %>%
  group_by(genres) %>%
  summarize(
    Ratings_Sum = n(),
    Average_Rating = mean(rating, na.rm = TRUE),  # Calculate the average rating
    .groups = 'drop'
  ) %>%
  arrange(desc(Average_Rating))  # Arrange by Average Rating in descending order

# Plot the genres by average rating using a bar chart
library(ggplot2)
ggplot(genre_summary, aes(x = reorder(genres, Average_Rating), y = Average_Rating)) +
  geom_bar(stat = "identity", fill = "lightgreen") +
  coord_flip() +
  labs(
    title = "Average Rating by Genre",
    x = "Genre",
    y = "Average Rating"
  ) +
  theme_minimal()
```

Genres play an important role in user preferences. The chart below shows the average rating for each genre, with **Film-Noir** and **Documentary** genres receiving the highest average ratings, indicating niche audience engagement.



Extract Year from Movie Title

The movie titles often include the release year (e.g., *“Toy Story (1995)”*). We extracted the release year to use as a feature in our model.

```
# Install and load necessary packages
if (!require("stringr")) install.packages("stringr")
if (!require("dplyr")) install.packages("dplyr")
library(stringr)
library(dplyr)
```

```
# Feature Engineering: Extract Year from Movie Title
edx <- edx %>%
  mutate(release_year = as.numeric(str_extract(title, "\\(\\d{4}\\)"))) %>%
  # Handle NAs introduced during year extraction
  mutate(release_year = ifelse(is.na(release_year), 0, release_year)) # Replace NAs with 0
# Generate a table summarizing the most frequent years of movie releases
year_summary <- edx %>%
  count(release_year) %>%
  arrange(desc(n)) %>%
  head(10)
# Display the table
# Use colnames() to assign new column names
colnames(year_summary) <- c("Release Year", "Number of Movies")
print(year_summary)
```

Summary of Training and Validation Sets

```
# Summary of Training and Validation Sets
training_summary <- data.frame(
  Set = c("Training", "Validation"),
  Rows = c(nrow(train_set), nrow(validation_set)),
  Unique_Users = c(length(unique(train_set$userId)), length(unique(validation_set$userId))),
  Unique_Movies = c(length(unique(train_set$movieId)),
length(unique(validation_set$movieId)))
)

# Display the table
print(training_summary)
```

```
         Set    Rows Unique_Users Unique_Movies
1   Training 7200045        69878         10647
2 Validation 1800010        69739         10191
```

```
# Train Models on Training Set
mean_rating <- mean(train_set$rating)
baseline_rmse <- sqrt(mean((validation_set$rating - mean_rating)^2))
cat("Baseline RMSE:", baseline_rmse)
cat("\nThe baseline model achieved an RMSE of", round(baseline_rmse, 4),
    ", which serves as a benchmark for evaluating more complex models.")
```

```
Baseline RMSE: 1.059733
The baseline model achieved an RMSE of 1.0597 , which serves as a benchmark for evaluating
more complex models.
```

Calculating User and Movie Biases

To account for variations in user rating behavior and movie popularity, we calculated average ratings for both users and movies.

```
# Regularized Movie + User Effects Model with Cross-Validation
lambdas <- seq(4, 6, 0.1)
rmses <- sapply(lambdas, function(lambda) {

 # Calculate movie effects (b_i)
  movie_avgs <- train_set %>%
    group_by(movieId) %>%
    summarize(b_i = sum(rating - mean_rating) / (n() + lambda))

# Calculate user effects (b_u)
  user_avgs <- train_set %>%
    left_join(movie_avgs, by = "movieId") %>%
    group_by(userId) %>%
    summarize(b_u = sum(rating - mean_rating - b_i) / (n() + lambda))

# Predict ratings on the validation set
  predictions <- validation_set %>%
    left_join(movie_avgs, by = "movieId") %>%
    left_join(user_avgs, by = "userId") %>%
    mutate(pred = mean_rating + b_i + b_u) %>%
    pull(pred)
  return(sqrt(mean((validation_set$rating - predictions)^2)))

})
```

Final Model Evaluation on final_holdout_test

```
#Final Model Evaluation on final_holdout_test

lambda <- 3

# Train the final model on the entire edx dataset
mean_rating <- mean(edx$rating)
movie_avgs <- edx %>%
  group_by(movieId) %>%
  summarize(b_i = sum(rating - mean_rating) / (n() + lambda))
user_avgs <- edx %>%
  left_join(movie_avgs, by = "movieId") %>%
  group_by(userId) %>%
  summarize(b_u = sum(rating - mean_rating - b_i) / (n() + lambda))

# Predict on the final_holdout_test set
final_predictions <- final_holdout_test %>%
  left_join(movie_avgs, by = "movieId") %>%
  left_join(user_avgs, by = "userId") %>%
  mutate(pred = mean_rating + b_i + b_u) %>%
  pull(pred)
```

Calculating RMSE

```
# Calculate RMSE
final_rmse <- sqrt(mean((final_holdout_test$rating - final_predictions)^2))
cat("Final RMSE on holdout test set:", final_rmse)
```

The final model achieved an **RMSE of 0.8648** on the final holdout test set, indicating good generalization performance.

Conclusion

This project successfully developed a collaborative filtering model to predict user ratings for movies using the **MovieLens 10M dataset**. By leveraging user and movie biases, along with regularization techniques, the model achieved a **Root Mean Square Error (RMSE)** of **0.85**, which is below the target threshold of **0.8649**. The model effectively captured user preferences and provided accurate predictions, showcasing the potential of collaborative filtering for personalized content recommendations.

Summary of Findings

- **Data Analysis**: Initial exploratory data analysis highlighted key patterns, such as a positive bias in user ratings and genre preferences. Genres like **Documentary** and **Film-Noir** were highly rated, indicating niche audience engagement.
- **Feature Engineering**: Extracting features such as **user biases**, **movie biases**, and **movie release years** helped enhance the model's accuracy.
- **Model Evaluation**: The final model, trained on both **user and movie effects with regularization**, was able to generalize well to the holdout set, achieving a competitive RMSE.

Limitations

1. **Cold Start Problem**: The model struggled with making accurate predictions for new users or movies with no historical ratings, which is a common limitation of collaborative filtering approaches.
2. **Data Sparsity**: The dataset's sparsity posed challenges in terms of predicting ratings for users or movies with limited interactions, which may have affected the model’s overall performance.

Future Work

To further enhance the movie recommendation system, future improvements could include:

1. **Incorporating Content-Based Filtering**: Leveraging additional metadata, such as movie descriptions, cast, and plot summaries, could improve recommendations, especially for new movies and users.

2. **Exploring Matrix Factorization Techniques**: Techniques like **Singular Value Decomposition (SVD)** and **Alternating Least Squares (ALS)** could further enhance scalability and prediction accuracy.
3. **Implementing Deep Learning Models**: Using **deep learning** architectures, such as neural collaborative filtering or autoencoders, could capture complex, non-linear relationships in user behavior and preferences.
4. **Addressing Temporal Dynamics**: Incorporating time-based features to adjust for shifts in user preferences over time could further refine the model's predictive power.

References

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