Recommender System for Movie Recommendations

The abundance of entertainment content options, such as movies, in the digital age can frequently leave users overwhelmed and unsure of what to view next. Recommender systems play an essential role in addressing this issue by providing personalized suggestions based on the preferences and behaviors of users. To enhance user experience and engagement, these systems are extensively implemented on numerous platforms, including streaming services, e-commerce websites, and social media platforms.

This report describes the design and construction of a MovieLens-based movie recommender system. The system's main purpose is to let users enter a movie they like and get recommendations for others. The system makes user-item interaction-based predictions using collaborative filtering, a proven recommendation method. Collaborative filtering is ideal for tailored movie suggestions since it predicts user preferences from a group of users.

Step 1: Load and Preprocess the Data

The initial phase of recommender system development involved importing and preprocessing the MovieLens dataset. This dataset contains user-provided movie ratings and metadata. The movies and ratings data were imported from their respective CSV files. Afterward, a merged dataset was created by combining movie and rating data. This merged dataset was utilized as the basis for the user-movie interaction matrix.

```
# Load required packages
library(tidyverse)

## ── Attaching packages ─────────────────────────────────────── tidyverse
1.3.2 ──
## ✓ ggplot2 3.4.2     ✓ purrr   1.0.1
## ✓ tibble  3.2.1     ✓ dplyr   1.1.2
## ✓ tidyr   1.3.0     ✓ stringr 1.5.0
## ✓ readr   2.1.4     ✓ forcats 1.0.0
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✕ dplyr::filter() masks stats::filter() ##
✕ dplyr::lag()    masks stats::lag()
library(caret)
```

```
## Loading required package: lattice ##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```
#  Load  the  MovieLens  dataset  movies   <-
read.csv("movies.csv")       ratings       <-
read.csv("ratings.csv")

#Merge movie and rating data
movielens <- left_join(ratings, movies, by = "movieId") head(movielens)
```

```
##   userId movieId rating timestamp                        title
## 1      1       1      4 964982703             Toy Story (1995)
## 2      1       3      4 964981247      Grumpier Old Men (1995)
## 3      1       6      4 964982224                  Heat (1995)
## 4      1      47      5 964983815 Seven (a.k.a. Se7en) (1995)
## 5      1      50      5 964982931  Usual Suspects, The (1995)
## 6      1      70      3 964982400  From Dusk Till Dawn (1996)
##                                        genres
## 1 Adventure|Animation|Children|Comedy|Fantasy
## 2                              Comedy|Romance
## 3                       Action|Crime|Thriller
## 4                            Mystery|Thriller
## 5                      Crime|Mystery|Thriller
## 6                     Action|Comedy|Horror|Thriller
```

Step 2: Model Evaluation

A small portion (10%) of the dataset is sampled as a validation set, while the remainder of the data is separated into a working set. The validation set is used to evaluate the efficacy of the recommender system in the future.

```
#Model Evaluation

#create the working and validation sets
set.seed(1)
validation_index <- sample(1:nrow(movielens),
0.1*nrow(movielens)) working_set <- movielens[-validation_index,]
temp <- movielens[validation_index,]

tibble(Dataset = c("movielens", "working_set", "temp"),
       "Number of ratings" = c(nrow(movielens), nrow(working_set),
nrow(temp)))
```

```
## # A tibble: 3 × 2
##   Dataset     `Number of ratings`
```

```
##   <chr>                          <int>
## 1 movielens                     100836
## 2 working_set                    90753
## 3 temp                           10083
```

Step 3: Verify Validation Set Data

Rows in the validation set containing userId and movieId that are absent from the working set are eliminated. This assures that only data from the working set are included in the validation set.

```
#Verify that userId and movieId from the validation set are also present in working_set

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

Step 4: Reintroduce Removed Rows

Reintroducing the rows removed from the validation set to the working set ensures that the working set is representative of the original data distribution.

```
#Reintroduce rows removed from the validation set to the working_set set
removed <- anti_join(temp, validation)

## Joining with `by = join_by(userId, movieId, rating, timestamp, title, genres)`

working_set <- rbind(working_set, removed)
str(working_set)

## 'data.frame':    91150 obs. of  6 variables:
##  $ userId   : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ movieId  : int  1 3 6 47 50 70 110 151 157 163 ...
##  $ rating   : num  4 4 4 5 5 3 4 5 5 5 ...
##  $ timestamp: int  964982703 964981247 964982224 964983815 964982931 964982400 964982176 964984041 964984100 964983650 ...
##  $ title    : chr  "Toy Story (1995)" "Grumpier Old Men (1995)" "Heat (1995)" "Seven (a.k.a. Se7en) (1995)" ...
##  $ genres   : chr  "Adventure|Animation|Children|Comedy|Fantasy" "Comedy|Romance" "Action|Crime|Thriller" "Mystery|Thriller" ...
```

Step 5: User Rating Analysis

A summary analysis of the number of ratings per user in the working set is conducted. This assists in comprehending the distribution of user engagement with the movies.

```
#Rating per user
working_set %>%
group_by(userId) %>%
```

```
  summarize(count = n()) %>%
slice_head(n = 10)
```

```
## # A tibble: 10 × 2
##    userId count
##     <int> <int>
##  1      1   202
##  2      2    22
##  3      3    38
##  4      4   198
##  5      5    39
##  6      6   278
##  7      7   141
##  8      8    38
##  9      9    41
## 10     10   125
```

```
#summary of user rating
summary(working_set %>% group_by(userId) %>% summarize(count = n()) %>%
select(count))
```

```
##      count
##  Min.   :  14.0
##  1st Qu.:  32.0
##  Median :  63.5
##  Mean   : 149.4
##  3rd Qu.: 155.0
##  Max.   :2435.0
```

Step 6: Movie Matrix Construction

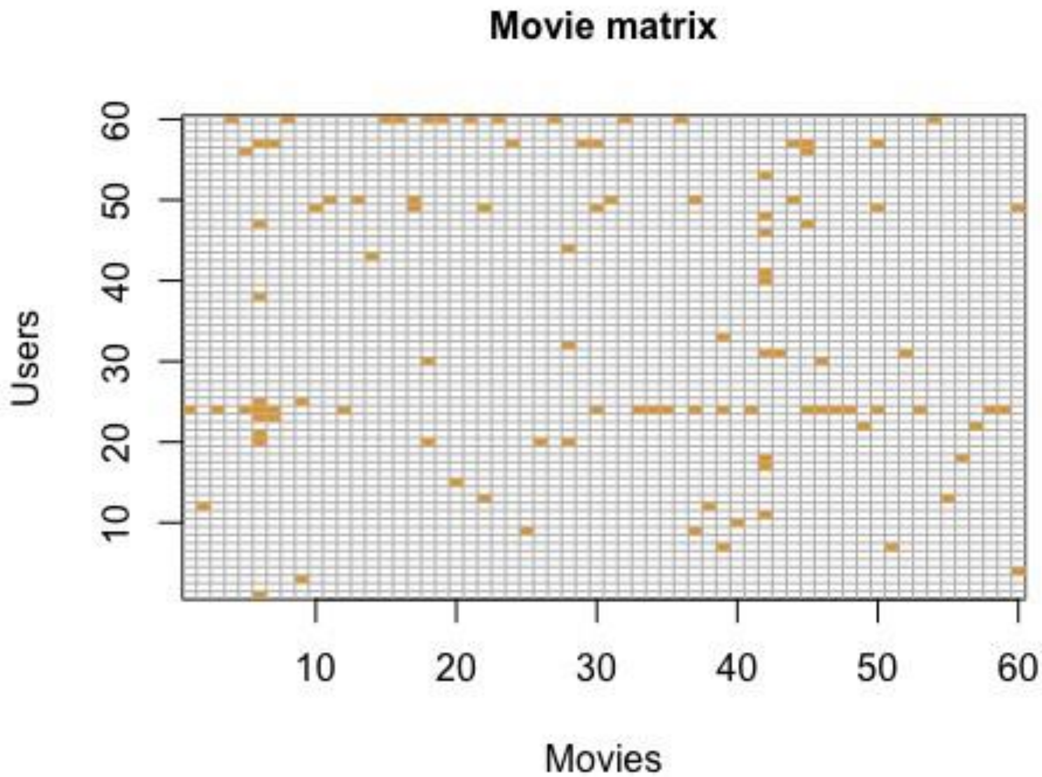
Each row represents a user, each column represents a movie, and the cell values indicate whether a user has rated a specific movie (1 if rated, 0 if not rated). The matrix is restricted to a predetermined number of users and films (limit).

```
#Movie matrix construction limit
<- 60
user_movie_matrix <- working_set %>%
  filter(userId %in% sample(unique(working_set$userId), limit))
%>%   select(userId, movieId, rating) %>%   mutate(rating = 1) %>%
spread(movieId, rating) %>%    select(sample(ncol(.), limit)) %>%
as.matrix() %>%



t(.)
```

Step 7: Movie Matrix Plot

Creating a plot of the user-movie matrix to visualize the ratings of movies by users. This plot provides an overview of how users are rating various films.

```
# Movie Matrix plot user_movie_matrix %>%     image(1:limit,
1:limit,., xlab = "Movies", ylab = "Users") +   abline(h =
0:limit + 0.5, v = 0:limit + 0.5, col = "grey") +   title(main
= list("Movie matrix", cex = 1, font = 2))
```




```
## integer(0)
```

Step 8: System Modeling - Training and Testing Sets

For system modeling, the dataset is divided into a training set (90 percent of the data) and a test set (10 percent of the data). Sampling is used to generate both training and test sets.

```
#
#System Modelling
#training index

set.seed(1)
train_index <- sample(1:nrow(movielens), 0.9*nrow(movielens)) train_set <-
movielens[train_index,]
temp_test_set <- movielens[-train_index,]

tibble(Dataset = c("movielens", "train_set", "temp_test_set"),
```

```r
       "Number of ratings" = c(nrow(movielens), nrow(train_set),
nrow(temp_test_set)))
```

```
## # A tibble: 3 × 2
##   Dataset       `Number of ratings`
##   <chr>                       <int>
## 1 movielens                  100836
## 2 train_set                   90752
## 3 temp_test_set               10084
```

```r
# testing index
set.seed(1)
test_index <- sample(1:nrow(movielens),
0.1*nrow(movielens)) train_set <- movielens[-test_index,]
temp_test_set <- movielens[test_index,]

tibble(Dataset = c("movielens", "train_set", "temp_test_set"),
"Number of ratings" = c(nrow(movielens), nrow(train_set),
nrow(temp_test_set)))
```

```
## # A tibble: 3 × 2
##   Dataset       `Number of ratings`
##   <chr>                       <int>
## 1 movielens                  100836
## 2 train_set                   90753
## 3 temp_test_set               10083
```

Step 9: Verify Test Set Data

Similar to the validation set, rows in the test set with userId and movieId that are not present in the training set are removed to ensure consistency in the data.

```r
# Verify that userId and movieId in the test set are also present in the
training set

test_set <- temp_test_set %>%
semi_join(train_set, by = "movieId") %>%
semi_join(train_set, by = "userId")

# Add rows eliminated from the test set to the training set.
removed <- anti_join(temp_test_set, test_set)
```

```
## Joining with `by = join_by(userId, movieId, rating, timestamp, title,
genres)`
```

```r
train_set <- rbind(train_set, removed)
```

Step 10: Random Guessing Model

A model of random guessing is established for comparison purposes. The model randomly estimates a rating for each user based on the distribution of ratings in the training set.

Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are utilized to evaluate this model's efficacy.

```
#Random guessing model and
predictions rating_range <- seq(0.5,
5, 0.5) guess_right <- function(x, y)
{   mean(y == x)
}

set.seed(1)
simulation <- replicate(10000, {
  i    <-     sample(train_set$rating,     1000,     replace     =     TRUE)
sapply(rating_range, guess_right, i)
})
guess_prob <- c()
for(i in 1:nrow(simulation)) {
  guess_prob <- append(guess_prob, mean(simulation[i,]))
}

y_hat_random <- sample(rating_range,
                       size =
nrow(validation),
replace = TRUE,                       prob =
guess_prob)


evaluation <- tibble(Model = c("Cinematch", "The Netflix Prize", "Random
guessing"),
                     MAE   =   c(NA,   NA,   Metrics::mae(validation$rating,
y_hat_random)),
                     MSE   =   c(NA,   NA,   Metrics::mse(validation$rating,
y_hat_random)),
                     RMSE  =  c(0.9525,  0.85725,
Metrics::rmse(validation$rating, y_hat_random)))
print(evaluation)

## # A tibble: 3 × 4
##   Model               MAE   MSE  RMSE
##   <chr>             <dbl> <dbl> <dbl>
## 1 Cinematch         NA    NA    0.952
## 2 The Netflix Prize NA    NA    0.857
## 3 Random guessing    1.15  2.16 1.47
```

Step 11: Linear Regression Model

Introduced is a linear regression model with a mean baseline. The predicted ratings are based on the training set's mean rating.

```
#Linear Regression Model
```

```
mu <- mean(train_set$rating)
y_hat_mean <- rep(mu, nrow(validation))

evaluation <- bind_rows(evaluation, tibble(Model = "Linear model (mean
baseline)",
                                           MAE =
Metrics::mae(validation$rating, y_hat_mean),
                                           MSE =
Metrics::mse(validation$rating, y_hat_mean),
                                           RMSE =
Metrics::rmse(validation$rating,    y_hat_mean)))
print(evaluation)
```

```
## # A tibble: 4 × 4
##   Model                          MAE   MSE  RMSE
##   <chr>                        <dbl> <dbl> <dbl>
## 1 Cinematch                   NA     NA    0.952
## 2 The Netflix Prize           NA     NA    0.857
## 3 Random guessing              1.15   2.16 1.47
## 4 Linear model (mean baseline)  0.812  1.04 1.02
```

Step 12: Movie Bias Calculation

The average rating deviation for each movie relative to the aggregate mean rating is determined to calculate movie bias.

```
#Movie bias per movie table bi_movie <- train_set %>%
group_by(movieId) %>%    summarize(bi_movie = mean(rating - mu),
bi_movie_isolated = mean(rating)) bi_movie %>% slice_head(n = 10)
```

```
## # A tibble: 10 × 3
##    movieId bi_movie bi_movie_isolated
##      <int>    <dbl>             <dbl>
##  1       1   0.423              3.92
##  2       2  -0.0604             3.44
##  3       3  -0.192              3.31
##  4       4  -1.20               2.3
##  5       5  -0.322              3.18
##  6       6   0.442              3.94
##  7       7  -0.272              3.23
##  8       8  -0.930              2.57
##  9       9  -0.434              3.07
## 10      10  -0.0139             3.49
```

Step 13: User Bias Calculation

User bias is computed by determining the average rating deviation for each user relative to the aggregate mean rating and the movie bias.

```
#Movie bias per user
bi_user <- train_set %>%
  left_join(bi_movie,    by    =    'movieId')    %>%
group_by(userId) %>%
  summarize(bi_user = mean(rating - mu - bi_movie),
bi_user_isolated    =    mean(rating))  bi_user    %>%
slice_head(n = 10)
```

```
## # A tibble: 10 × 3
##    userId  bi_user bi_user_isolated
##     <int>    <dbl>            <dbl>
##  1      1  0.828               4.40
##  2      2 -0.0628              3.93
##  3      3 -1.12                2.49
##  4      4 -0.226               3.54
##  5      5 -0.0345              3.67
##  6      6  0.307               3.51
##  7      7 -0.259               3.23
##  8      8 -0.0826              3.45
##  9      9 -0.00810             3.32
## 10     10 -0.189               3.28
```

Step 14: Linear Model with User and Movie Bias

A linear model is constructed to predict ratings for the validation set using the mean rating, movie bias, and user bias. For this model, the performance metrics are calculated.

```
#Linear model(mean + movie bias + user bias)

y_hat_bi_user    <-    validation    %>%
left_join(bi_movie,  by='movieId')  %>%
left_join(bi_user, by='userId') %>%
  mutate(y_hat = mu + bi_movie + bi_user) %>%
.$y_hat

evaluation <- bind_rows(evaluation,
                        tibble(Model = "Linear model (mean + movie and user
bias)",
                               MAE = Metrics::mae(validation$rating,
y_hat_bi_user),
                               MSE = Metrics::mse(validation$rating,
y_hat_bi_user),
                               RMSE = Metrics::rmse(validation$rating,
y_hat_bi_user))) print(evaluation)
```

```
## # A tibble: 5 × 4
##   Model                                          MAE    MSE   RMSE
##   <chr>                                        <dbl>  <dbl> <dbl>
## 1 Cinematch                                   NA     NA     0.952
## 2 The Netflix Prize                           NA     NA     0.857
```

```
## 3 Random guessing                             1.15   2.16  1.47
## 4 Linear model (mean baseline)                0.812  1.04  1.02  ##
5 Linear model (mean + movie and user bias)  0.664  0.754 0.868
```

Step 15: Top 10 Movie Recommendations

The top 10 movie recommendations for the test set are derived using a linear model with user and movie bias. The titles of the selected films are depicted in a data frame based on their predicted ratings.

```
#Top 10 Movies Recommendations top10 <-
test_set %>%  left_join(bi_movie, by =
"movieId") %>%  left_join(bi_user, by =
"userId") %>%  mutate(y_hat = mu + bi_movie
+ bi_user) %>%  arrange(desc(y_hat)) %>%
select(title) %>%  unique() %>%
slice_head(n = 10)
top10_df <- data.frame(Title = top10,
                               Rating = rep(NA, 10),
                               Count = rep(NA, 10))

print(top10_df)

##                                             title Rating Count
## 1  Children of the Corn IV: The Gathering (1996)     NA    NA
## 2                Machete Kills (Machete 2) (2013)     NA    NA
## 3                                    Logan (2017)     NA    NA
## 4                Shawshank Redemption, The (1994)     NA    NA
## 5                         Lion King 1½, The (2004)     NA    NA
## 6                    Trial, The (Procès, Le) (1962)     NA    NA
## 7  Like Stars on Earth (Taare Zameen Par) (2007)     NA    NA
## 8                              Rough Night (2017)     NA    NA
## 9                               Fight Club (1999)     NA    NA
## 10                   The Man from Nowhere (2010)     NA    NA
```

Conclusion

The report illustrates the construction of a recommender system based on a linear model with user and movie bias. It includes data preprocessing, model training and testing, bias calculation, and performance evaluation of various models. The recommendations are derived using the linear model and the predicted ratings. **References**

https://www.kaggle.com/code/amirmotefaker/movie-recommendation-system-using-rbest