```
<!--
DPA Project - Movie Recommendation System

Group members:
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```

Importing Libraries

```
library(zoo)
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(tidyr)
library(caret)
```

```
## Loading required package: lattice
```

```
library(FNN)
library(rpart)
library(ROCR)
library(class)
```

```
##
## Attaching package: 'class'
```

```
## The following objects are masked from 'package:FNN':
##
##     knn, knn.cv
```

Importing Dataset

```
# Loading movies dataset
movies_dataset <- read.table("title.basics.tsv",
                   header = TRUE,
                   sep = "\t",
                   quote = "",
                   na.strings = "\\N",
                   stringsAsFactors = FALSE,
                   fill = TRUE)
```

```
head(movies_dataset)
```

```
##      tconst titleType           primaryTitle          originalTitle isAdult
## 1 tt0000001     short             Carmencita             Carmencita       0
## 2 tt0000002     short Le clown et ses chiens Le clown et ses chiens       0
## 3 tt0000003     short         Pauvre Pierrot         Pauvre Pierrot       0
## 4 tt0000004     short            Un bon bock            Un bon bock       0
## 5 tt0000005     short       Blacksmith Scene       Blacksmith Scene       0
## 6 tt0000006     short      Chinese Opium Den      Chinese Opium Den       0
##   startYear endYear runtimeMinutes                   genres
## 1      1894      NA              1        Documentary,Short
## 2      1892      NA              5          Animation,Short
## 3      1892      NA              4 Animation,Comedy,Romance
## 4      1892      NA             12          Animation,Short
## 5      1893      NA              1             Comedy,Short
## 6      1894      NA              1                    Short
```

```
# Summary Statistics of movies dataset
summary(movies_dataset)
```

```
##     tconst           titleType         primaryTitle       originalTitle
##  Length:10565899    Length:10565899    Length:10565899    Length:10565899
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##     isAdult          startYear          endYear         runtimeMinutes
##  Min.   :0         Min.   :1874      Min.   :1906       Min.   :    0
##  1st Qu.:0         1st Qu.:2003      1st Qu.:1999       1st Qu.:   15
##  Median :0         Median :2013      Median :2013       Median :   30
##  Mean   :0         Mean   :2006      Mean   :2007       Mean   :   45
##  3rd Qu.:0         3rd Qu.:2018      3rd Qu.:2019       3rd Qu.:   60
##  Max.   :1         Max.   :2031      Max.   :2030       Max.   :54321
##  NA's   :3574702   NA's   :3857911   NA's   :10447068   NA's   :8050542
##     genres
##  Length:10565899
##  Class :character
##  Mode  :character
##
##
##
##
```

```
# Structure of the movies dataset
str(movies_dataset)
```

```
## 'data.frame':    10565899 obs. of  9 variables:
##  $ tconst        : chr  "tt0000001" "tt0000002" "tt0000003" "tt0000004" ...
##  $ titleType     : chr  "short" "short" "short" "short" ...
##  $ primaryTitle  : chr  "Carmencita" "Le clown et ses chiens" "Pauvre Pierrot" "Un bo
n bock" ...
##  $ originalTitle : chr  "Carmencita" "Le clown et ses chiens" "Pauvre Pierrot" "Un bo
n bock" ...
##  $ isAdult       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ startYear     : int  1894 1892 1892 1892 1893 1894 1894 1894 1894 1895 ...
##  $ endYear       : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ runtimeMinutes: int  1 5 4 12 1 1 1 1 45 1 ...
##  $ genres        : chr  "Documentary,Short" "Animation,Short" "Animation,Comedy,Roman
ce" "Animation,Short" ...
```

```
# Loading ratings dataset
ratings_dataset <- read.table("title.ratings.tsv", header = TRUE, fill = TRUE)
```

```
head(ratings_dataset)
```

```
##      tconst averageRating numVotes
## 1 tt0000001           5.7     2024
## 2 tt0000002           5.7      272
## 3 tt0000003           6.5     1962
## 4 tt0000004           5.4      178
## 5 tt0000005           6.2     2727
## 6 tt0000006           5.0      184
```

```
# Summary Statistics of ratings dataset
summary(ratings_dataset)
```

```
##     tconst          averageRating       numVotes
##  Length:1403737     Min.   : 1.000   Min.   :      5
##  Class :character   1st Qu.: 6.200   1st Qu.:     11
##  Mode  :character   Median : 7.100   Median :     26
##                     Mean   : 6.956   Mean   :   1037
##                     3rd Qu.: 7.900   3rd Qu.:    101
##                     Max.   :10.000   Max.   :2858177
```

```
# Structure of the ratings dataset
str(ratings_dataset)
```

```
## 'data.frame':    1403737 obs. of  3 variables:
##  $ tconst       : chr  "tt0000001" "tt0000002" "tt0000003" "tt0000004" ...
##  $ averageRating: num  5.7 5.7 6.5 5.4 6.2 5 5.4 5.4 5.3 6.8 ...
##  $ numVotes     : int  2024 272 1962 178 2727 184 847 2172 209 7449 ...
```

Droping unnecessary columns

```
final_movies_dataset <- subset(movies_dataset, select = -c(primaryTitle, originalTitle,
endYear))
head(final_movies_dataset)
```

```
##      tconst titleType isAdult startYear runtimeMinutes                  genres
## 1 tt0000001     short       0      1894              1        Documentary,Short
## 2 tt0000002     short       0      1892              5          Animation,Short
## 3 tt0000003     short       0      1892              4 Animation,Comedy,Romance
## 4 tt0000004     short       0      1892             12          Animation,Short
## 5 tt0000005     short       0      1893              1             Comedy,Short
## 6 tt0000006     short       0      1894              1                    Short
```

Merging two datasets

```
final_dataset <- merge(final_movies_dataset, ratings_dataset, by = "tconst", all.x = TRU
E)
```

```
head(final_dataset)
```

```
##      tconst titleType isAdult startYear runtimeMinutes                  genres
## 1 tt0000001     short       0      1894              1        Documentary,Short
## 2 tt0000002     short       0      1892              5          Animation,Short
## 3 tt0000003     short       0      1892              4 Animation,Comedy,Romance
## 4 tt0000004     short       0      1892             12          Animation,Short
## 5 tt0000005     short       0      1893              1             Comedy,Short
## 6 tt0000006     short       0      1894              1                   Short
##   averageRating numVotes
## 1           5.7     2024
## 2           5.7      272
## 3           6.5     1962
## 4           5.4      178
## 5           6.2     2727
## 6           5.0      184
```

Handling null values

```
null_counts <- sapply(final_dataset, function(x) sum(is.na(x)))
print(null_counts)
```

```
##         tconst      titleType        isAdult      startYear runtimeMinutes
##              0              0        3574702        3857911        8050542
##         genres  averageRating       numVotes
##         291312        9162163        9162163
```

Null values in isAdult

```
#Considering those null values as not adult movies
final_dataset$isAdult <- ifelse(is.na(final_dataset$isAdult), 0, final_dataset$isAdult)
```

Null values in startYear

```
#Filling the null values in startYear field with the previous non-null entry value. Cons
idering the movie is relased in same year
final_dataset$startYear <- na.locf(final_dataset$startYear)
```

Null values in runtimeMinutes

```
# Remove rows with missing runtime values
temp_ds <- final_dataset[!is.na(final_dataset$runtimeMinutes), ]

# Calculate average runtime for each title type
average_runtime <- tapply(temp_ds$runtimeMinutes, temp_ds$titleType, mean)

# Convert average runtime to integer
average_runtime <- round(average_runtime)

# Replacing null values with the average value of corresponding titletype

for(tt in unique(final_dataset$titleType)) {
  null_indices <- is.na(final_dataset$runtimeMinutes) & final_dataset$titleType == tt
  final_dataset$runtimeMinutes[null_indices] <- average_runtime[tt]
}
```

```
# Check for null values in the runtimeMinutes column
null_indices <- which(is.na(final_dataset$runtimeMinutes))

# Print rows with null values in the runtimeMinutes column
print(final_dataset[null_indices, ])
```

```
##            tconst titleType isAdult startYear runtimeMinutes genres
## 3834477 tt15258334   tvPilot       0      1991            NA   <NA>
##         averageRating numVotes
## 3834477            NA       NA
```

```
unique_runtimes <- unique(final_dataset$titleType)
# Print the unique values
print(unique_runtimes)
```

```
##  [1] "short"        "movie"        "tvShort"      "tvMovie"      "tvSeries"
##  [6] "tvEpisode"    "tvMiniSeries" "tvSpecial"    "video"        "videoGame"
## [11] "tvPilot"
```

```
final_dataset <- final_dataset[final_dataset$titleType != "tvPilot", ]
```

Null values in AverageRating and nuumVotes

```
# Remove rows with null values in the averageRating column
final_dataset <- final_dataset[complete.cases(final_dataset$averageRating), ]
```

Null values in Genres

```
# Replacing null values with other in the genres column
final_dataset$genres[is.na(final_dataset$genres)] <- 'other,'
```

```
null_counts <- sapply(final_dataset, function(x) sum(is.na(x)))
print(null_counts)
```

```
##         tconst      titleType        isAdult      startYear runtimeMinutes
##              0              0              0              0              0
##         genres  averageRating       numVotes
##              0              0              0
```

```
num_rows <- nrow(final_dataset)

# Print the number of rows
print(num_rows)
```

```
## [1] 1403736
```

Data Exploration

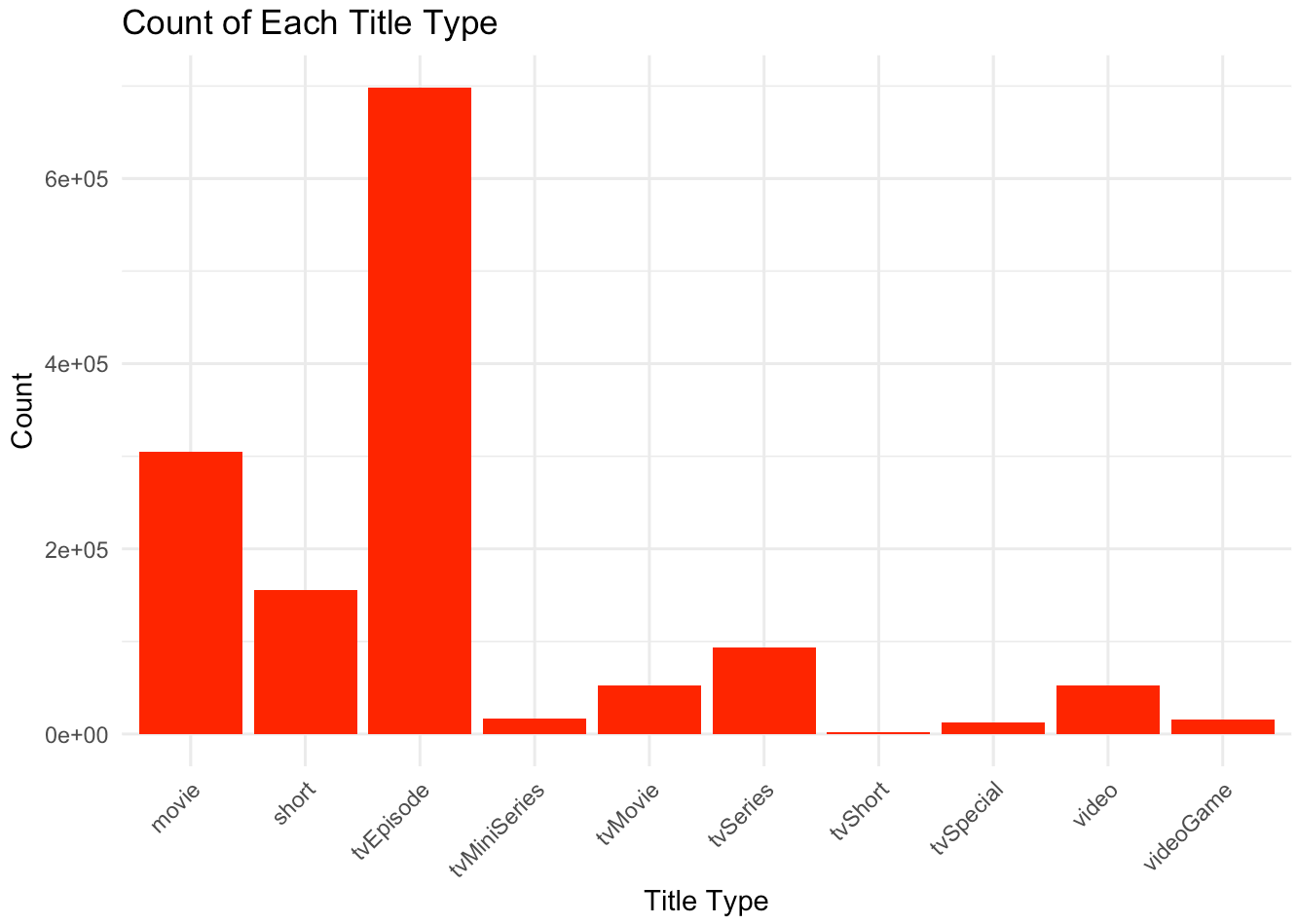
```
# Unique values of feature titleType
distinct_title_types <- unique(final_dataset$titleType)
print(distinct_title_types)
```

```
##  [1] "short"        "movie"        "tvShort"      "tvMovie"      "tvSeries"
##  [6] "tvEpisode"    "tvMiniSeries" "tvSpecial"    "video"        "videoGame"
```

```
# Count the occurrences of each value in the titleType column
title_type_counts <- as.data.frame(table(final_dataset$titleType))

print(title_type_counts)
```

```
##            Var1   Freq
## 1         movie 304790
## 2         short 155700
## 3     tvEpisode 698229
## 4  tvMiniSeries  16689
## 5       tvMovie  52263
## 6      tvSeries  93344
## 7       tvShort   2279
## 8     tvSpecial  12100
## 9         video  52437
## 10    videoGame  15905
```

```
# Plot the graph using ggplot2
ggplot(title_type_counts, aes(x = Var1, y = Freq)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(title = "Count of Each Title Type",
       x = "Title Type",
       y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

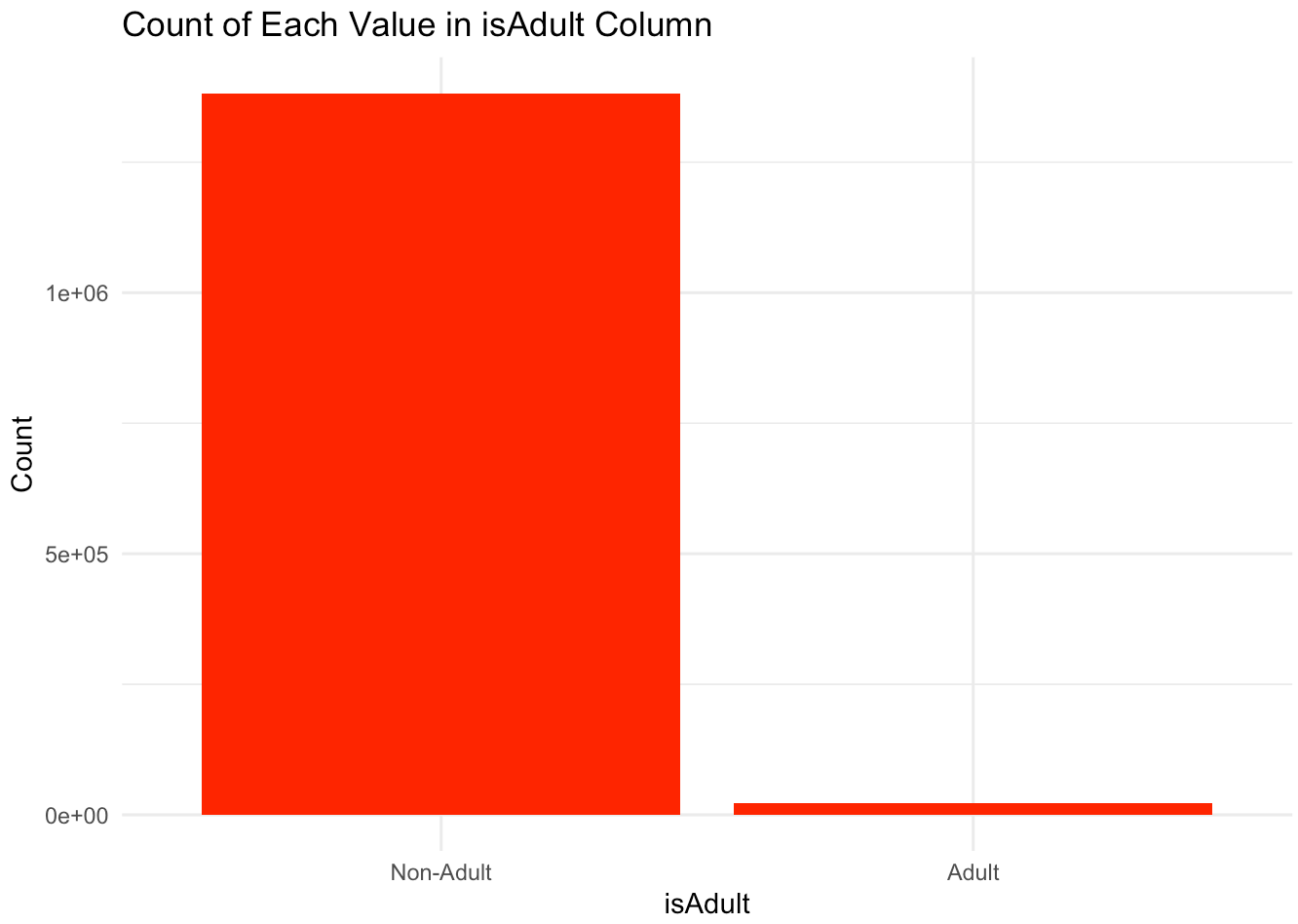


Most of the movies belongs to tvEpisodes

```
# Unique values of feature titleType
is_adult_counts <- as.data.frame(table(final_dataset$isAdult))

print(is_adult_counts)
```

```
##   Var1    Freq
## 1    0 1381769
## 2    1   21967
```

```
# Plot the graph using ggplot2
ggplot(is_adult_counts, aes(x = factor(Var1), y = Freq)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(title = "Count of Each Value in isAdult Column",
       x = "isAdult",
       y = "Count") +
  scale_x_discrete(labels = c("Non-Adult", "Adult")) + theme_minimal()
```




```
# Split the strings in the genres column by comma and convert to list
final_dataset$genres <- strsplit(final_dataset$genres, ",")
```

```
head(final_dataset)
```

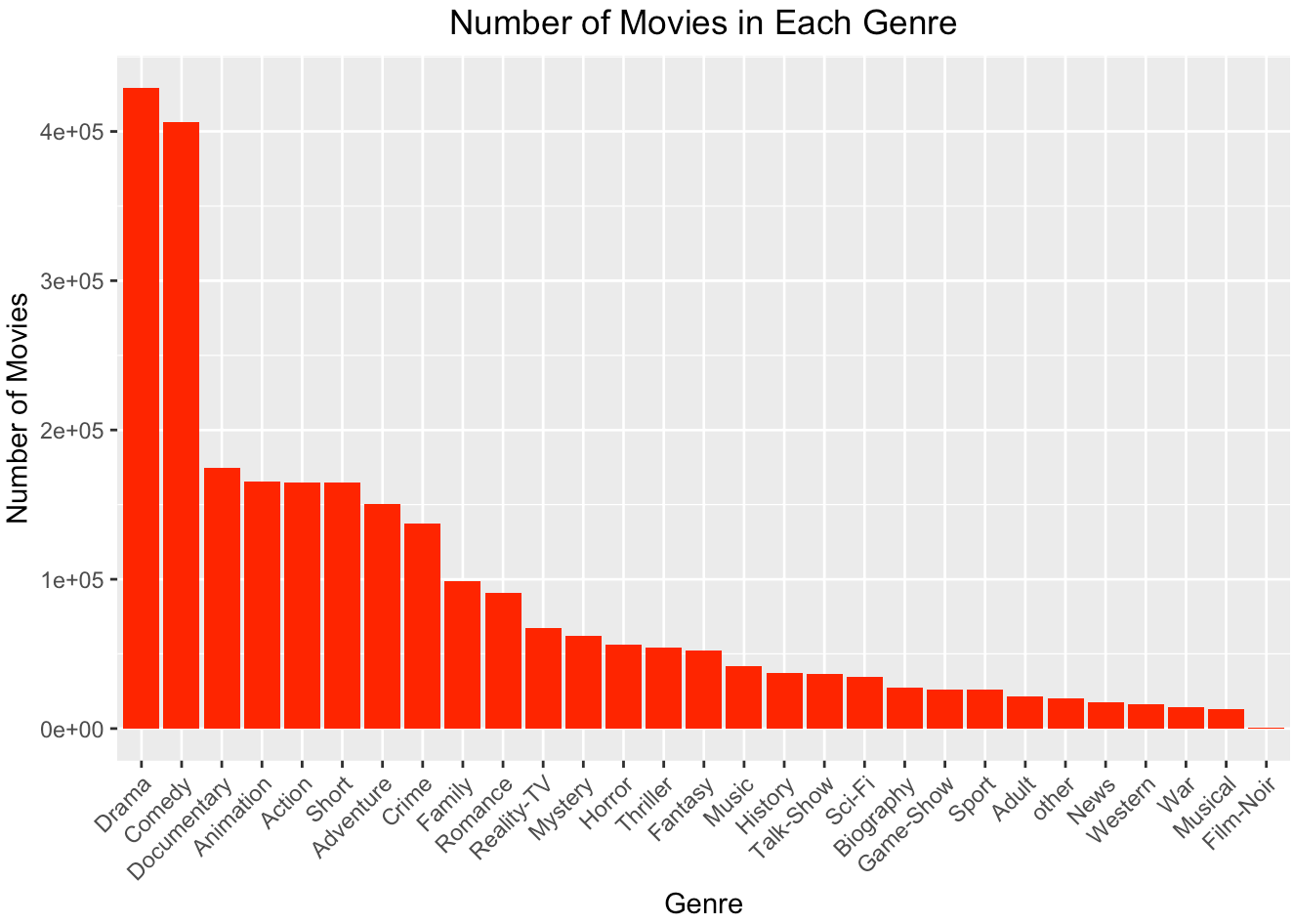
```
##      tconst titleType isAdult startYear runtimeMinutes
## 1 tt0000001     short       0      1894              1
## 2 tt0000002     short       0      1892              5
## 3 tt0000003     short       0      1892              4
## 4 tt0000004     short       0      1892             12
## 5 tt0000005     short       0      1893              1
## 6 tt0000006     short       0      1894              1
##                       genres averageRating numVotes
## 1         Documentary, Short           5.7     2024
## 2           Animation, Short           5.7      272
## 3 Animation, Comedy, Romance           6.5     1962
## 4           Animation, Short           5.4      178
## 5              Comedy, Short           6.2     2727
## 6                      Short           5.0      184
```

Number of movies in each genre

```
# Unnest the genres column to create separate rows for each genre
unnested_gendata <- final_dataset %>%
  unnest(genres)

# Count the number of movies in each genre
genre_counts <- unnested_gendata %>%
  group_by(genres) %>%
  summarise(num_movies = n()) %>%
  arrange(desc(num_movies))

print(genre_counts)
```

```
## # A tibble: 29 × 2
##    genres      num_movies
##    <chr>            <int>
##  1 Drama           429382
##  2 Comedy          406012
##  3 Documentary     174480
##  4 Animation       165657
##  5 Action          164897
##  6 Short           164682
##  7 Adventure       150133
##  8 Crime           137656
##  9 Family           98860
## 10 Romance          91074
## # ℹ 19 more rows
```

```
# Plot the graph
ggplot(genre_counts, aes(x = reorder(genres, -num_movies), y = num_movies)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(title = "Number of Movies in Each Genre",
       x = "Genre",
       y = "Number of Movies") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        plot.title = element_text(hjust = 0.5))
```



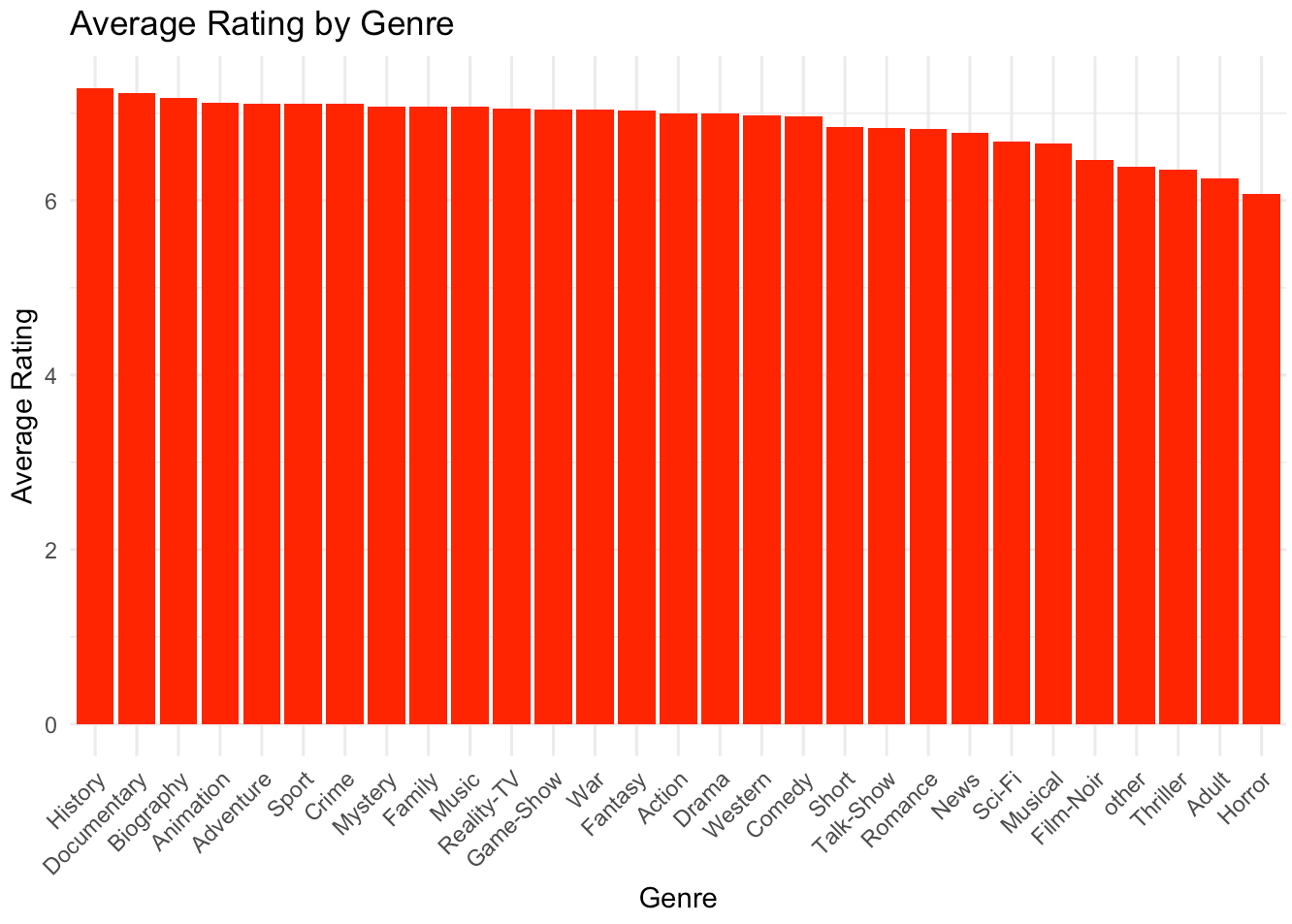
Most of the movies given in the dataset are belongs to Drama genre (429382) and least number of movies are Film-Noir (880)

Average ratings for each genres

```
# Group by genre and calculate the average rating
average_ratings_by_genre <- unnested_gendata %>%
  group_by(genres) %>%
  summarise(average_rating = mean(averageRating, na.rm = TRUE)) %>%
  arrange(desc(average_rating))

# Print the top-rated genres
print(average_ratings_by_genre)
```

```
## # A tibble: 29 × 2
##    genres      average_rating
##    <chr>                <dbl>
##  1 History               7.29
##  2 Documentary           7.24
##  3 Biography             7.18
##  4 Animation             7.12
##  5 Adventure             7.11
##  6 Sport                 7.11
##  7 Crime                 7.11
##  8 Mystery               7.08
##  9 Family                7.08
## 10 Music                 7.08
## # ℹ 19 more rows
```

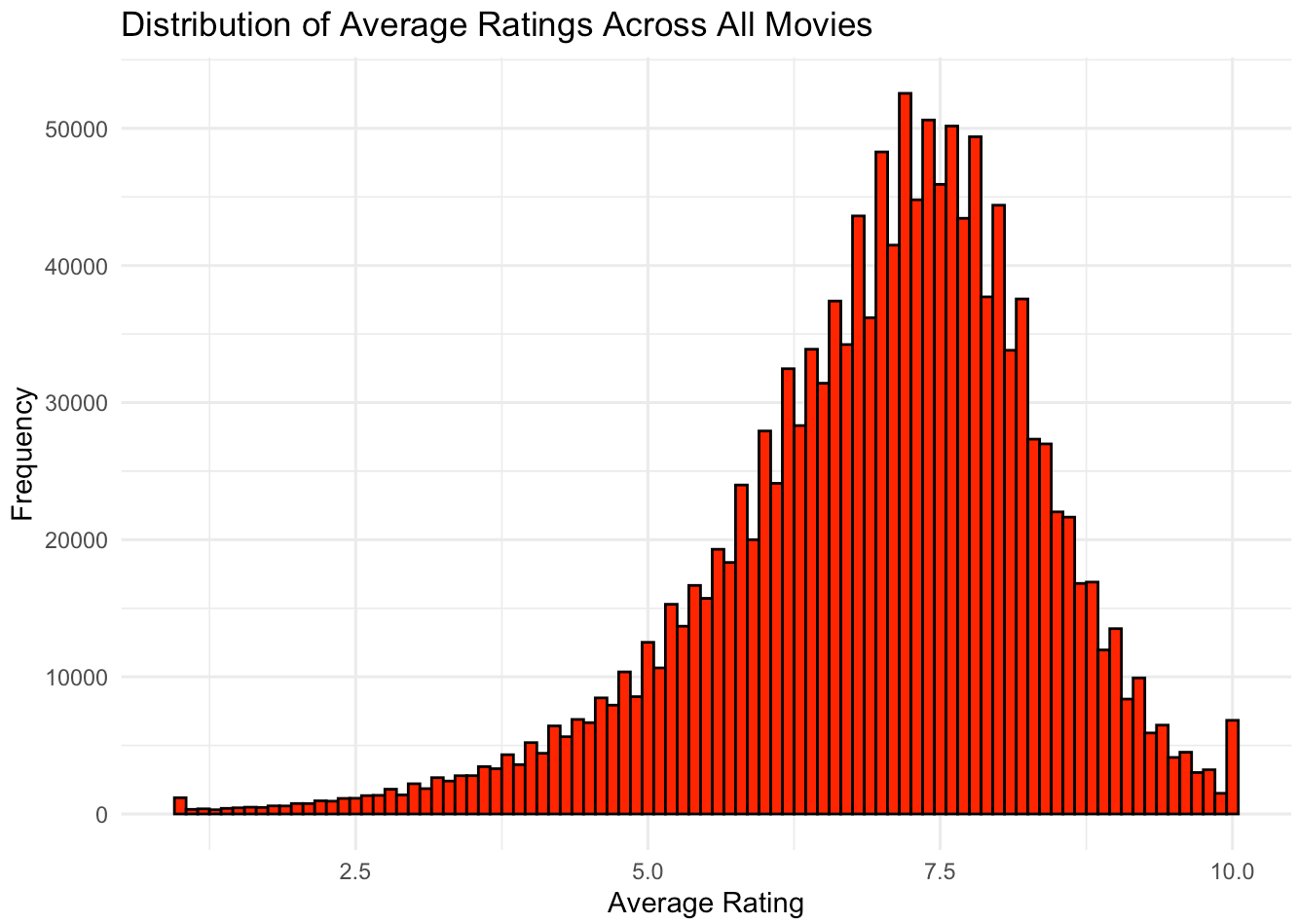
```
# Plot the graph
ggplot(average_ratings_by_genre, aes(x = reorder(genres, -average_rating), y = average_r
ating)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(title = "Average Rating by Genre",
       x = "Genre",
       y = "Average Rating") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Here, the average rating for all the genres is around 6 to 7 Movies belongs to History genre got highest average rating (7.289976) and movies belongs to Horror genre got least average rating (6.080079)

Distribution of average ratings across all movies

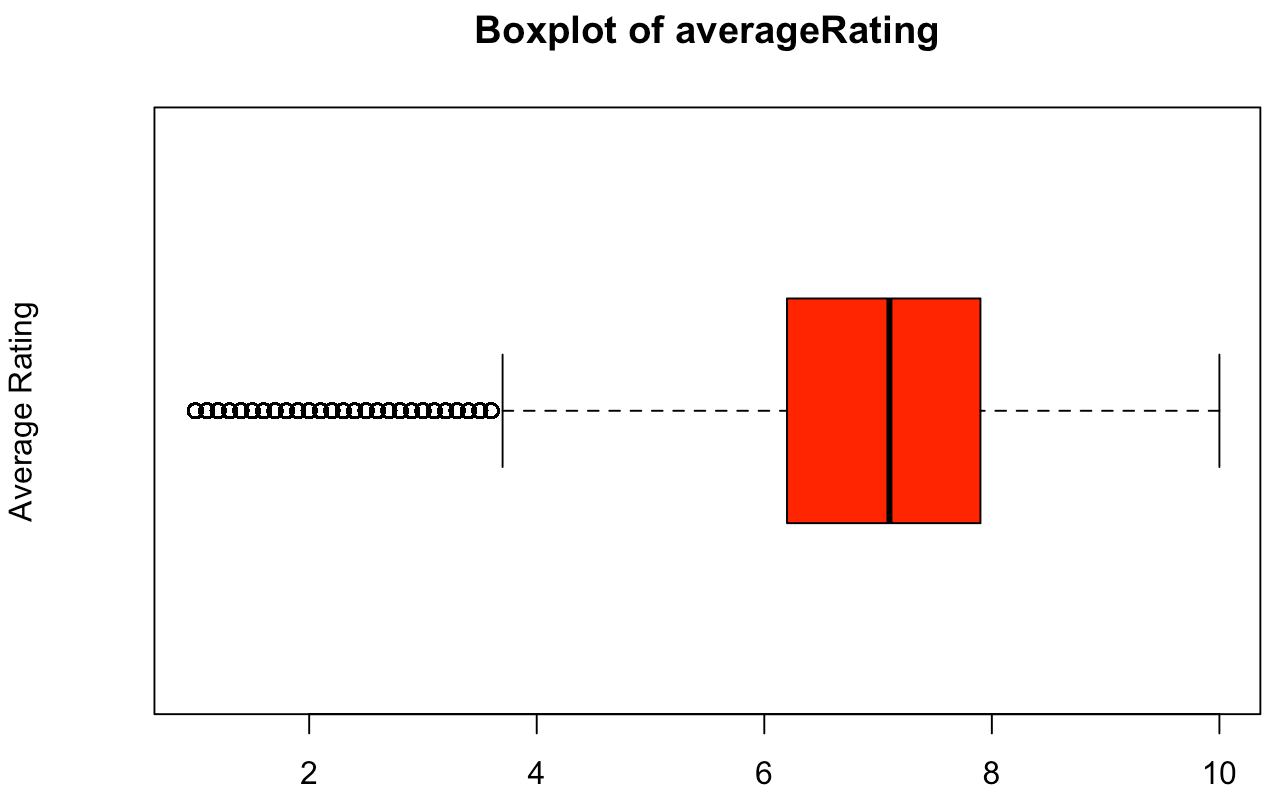
```
# Plot histogram of average ratings to distribution of average ratings across all movies
ggplot(final_dataset, aes(x = averageRating)) +
  geom_histogram(binwidth = 0.1, fill = "red", color = "black") +
  labs(title = "Distribution of Average Ratings Across All Movies",
       x = "Average Rating",
       y = "Frequency") +
  theme_minimal()
```



Here, most of the movies are rated around 7.5

Checking outliers for the averageRating feature

```
# Plot a boxplot for the averageRating feature
boxplot(final_dataset$averageRating,
        main = "Boxplot of averageRating",
        ylab = "Average Rating",
        col = "red",
        border = "black",
        horizontal = TRUE)
```



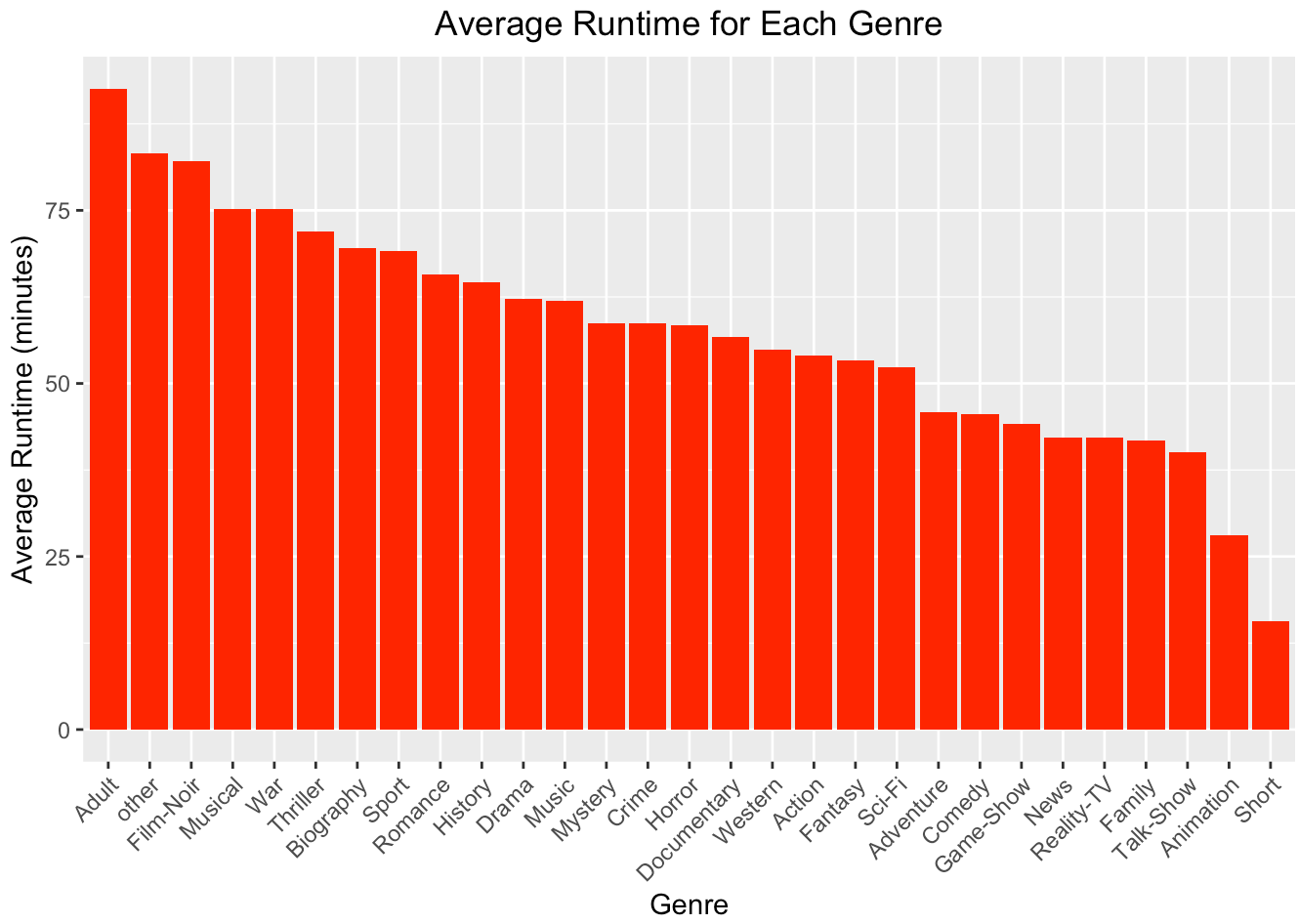
There are very less amount of outliers. Most of the ratings in between 6 to 8

Average Runtime for each genres

```
# Group by genre and calculate the average runtime
average_runtime_by_genre <- unnested_gendata %>%
  group_by(genres) %>%
  summarise(average_runtime = mean(runtimeMinutes, na.rm = TRUE)) %>%
  arrange(desc(average_runtime))

print(average_runtime_by_genre)
```

```
## # A tibble: 29 × 2
##    genres    average_runtime
##    <chr>               <dbl>
##  1 Adult                92.6
##  2 other                83.3
##  3 Film-Noir            82.1
##  4 Musical              75.2
##  5 War                  75.2
##  6 Thriller             72.0
##  7 Biography            69.5
##  8 Sport                69.1
##  9 Romance              65.7
## 10 History              64.6
## # ℹ 19 more rows
```

```
# Plot graph
ggplot(average_runtime_by_genre, aes(x = reorder(genres, -average_runtime), y = average_
runtime)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(title = "Average Runtime for Each Genre",
       x = "Genre",
       y = "Average Runtime (minutes)") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        plot.title = element_text(hjust = 0.5))
```



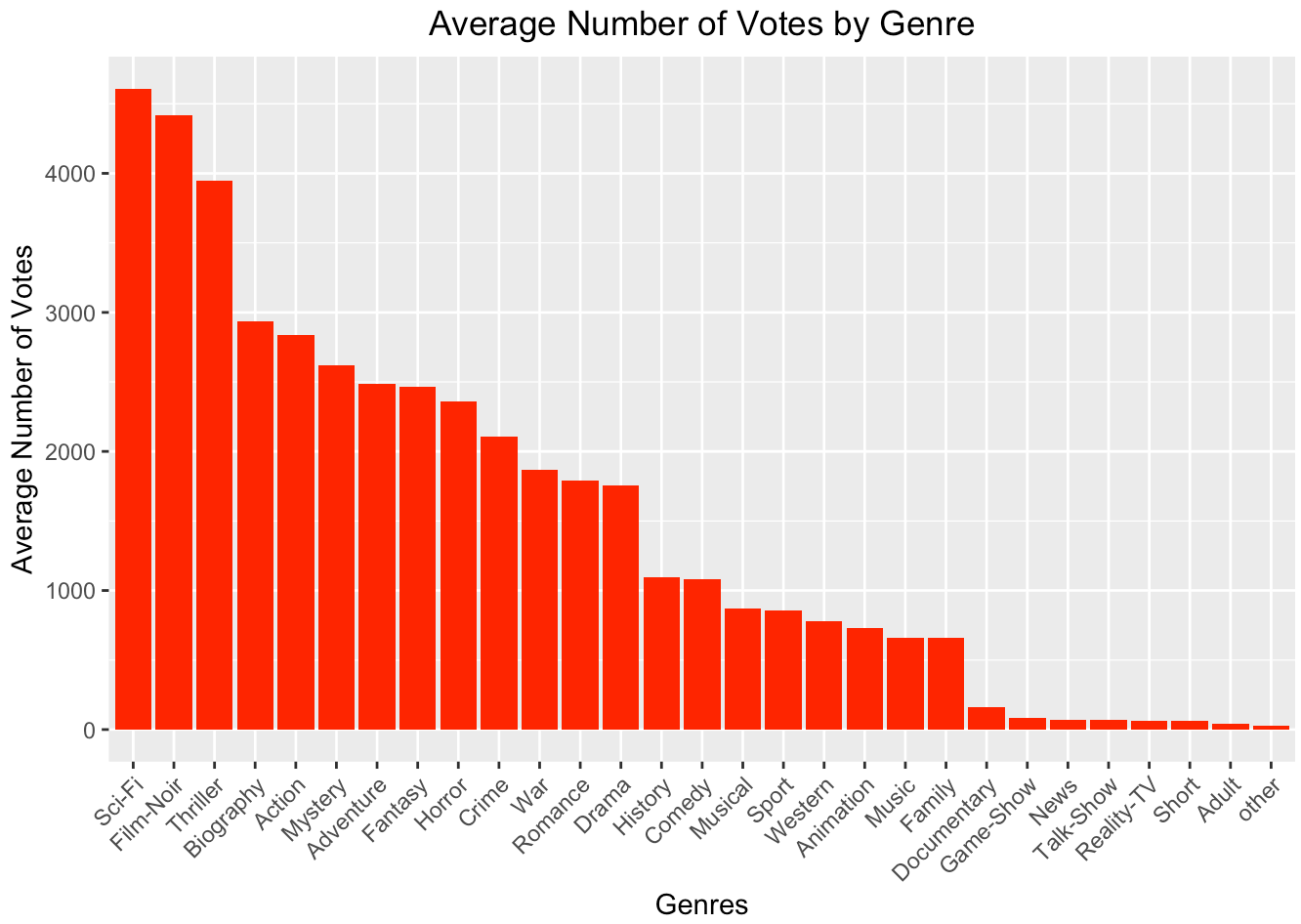
Longest average rumtime movies are belongs to Adult genre (92.60358 mins) and shortest average rumtime movies are belongs to short genre (15.66562 mins)

Which genres receive the highest number of votes on average?

```
# Group by genre and calculate the average number of votes
average_votes_by_genre <- unnested_gendata %>%
  group_by(genres) %>%
  summarise(average_votes = mean(numVotes))

# Arrange in descending order based on the average number of votes
average_votes_by_genre <- average_votes_by_genre %>%
  arrange(desc(average_votes))

average_votes_by_genre$average_votes = round(average_votes_by_genre$average_votes)
# Print the result
print(average_votes_by_genre)
```

```
## # A tibble: 29 × 2
##    genres    average_votes
##    <chr>             <dbl>
##  1 Sci-Fi             4610
##  2 Film-Noir          4417
##  3 Thriller           3944
##  4 Biography          2937
##  5 Action             2835
##  6 Mystery            2621
##  7 Adventure          2486
##  8 Fantasy            2467
##  9 Horror             2361
## 10 Crime              2109
## # ℹ 19 more rows
```

```
# Plot a graph
ggplot(average_votes_by_genre, aes(x = reorder(genres, -average_votes), y = average_vote
s)) +
  geom_bar(stat = "identity", fill = "red") +
  labs(title = "Average Number of Votes by Genre",
       x = "Genres",
       y = "Average Number of Votes") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        plot.title = element_text(hjust = 0.5))
```



On average, Sci-Fi genre recieved highest number of votes (4610) and other genre recieved lowest number of votes (27).

what kind of movies are most produced in yearly based

```
# Unnest the genres column to create separate rows for each genre
unnested_data <- final_dataset %>%
  unnest(genres)

# Group by startYear and genre, then count the occurrences
genre_counts <- unnested_data %>%
  group_by(startYear, genres, .drop = FALSE) %>%
  summarise(count = n(), .groups = "keep")

# Find the most produced genre for each year
most_produced_genre <- genre_counts %>%
  group_by(startYear) %>%
  slice(which.max(count)) %>%
  ungroup()

# Print the result
print(most_produced_genre)
```

```
## # A tibble: 145 × 3
##    startYear genres      count
##        <int> <chr>       <int>
##  1      1874 Documentary     2
##  2      1877 Animation       4
##  3      1878 Short           3
##  4      1881 Short           2
##  5      1882 Documentary     2
##  6      1883 Documentary     1
##  7      1885 Animation       1
##  8      1887 Short          45
##  9      1888 Short           5
## 10      1889 Short           2
## # ℹ 135 more rows
```

These are the genres that are most produced in each year

what kind of movies are most classified as adult content

```
# Count the occurrences of adult content for each genre
adult_genre_counts <- final_dataset %>%
  filter(isAdult == 1) %>%
  unnest(genres) %>%
  group_by(genres) %>%
  summarise(num_adult_movies = n()) %>%
  arrange(desc(num_adult_movies))

# Print the result
print(adult_genre_counts)
```

```
## # A tibble: 27 × 2
##    genres    num_adult_movies
##    <chr>                <int>
##  1 Adult                21211
##  2 Drama                 2277
##  3 Comedy                2042
##  4 Romance               1897
##  5 Crime                  643
##  6 Fantasy                609
##  7 Animation              431
##  8 Short                  406
##  9 other                  362
## 10 Horror                 330
## # ℹ 17 more rows
```

Most classified movies as adult content are belongs to Adult genre

Top-rated movies interms of avg rating & Numvotes

```
# Rank movies based on average rating and numVotes
top_rated_movies <- final_dataset %>%
  arrange(desc(averageRating), desc(numVotes)) %>%
  slice(1:10)  # Select the top 10 movies

# Print the top-rated movies
head(top_rated_movies)
```

```
##       tconst titleType isAdult startYear runtimeMinutes                 genres
## 1  tt2301451 tvEpisode       0      2013             47 Crime, Drama, Thriller
## 2 tt30643438     short       0      2023              2                  Short
## 3 tt29902774 tvEpisode       0      2021             37        News, Talk-Show
## 4 tt13688764 tvEpisode       0      2020             37
## 5 tt31029309     movie       0      2024            102            Documentary
## 6 tt29466076     short       0      2021             13                  Short
##   averageRating numVotes
## 1            10   212163
## 2            10     1153
## 3            10      986
## 4            10      961
## 5            10      769
## 6            10      742
```

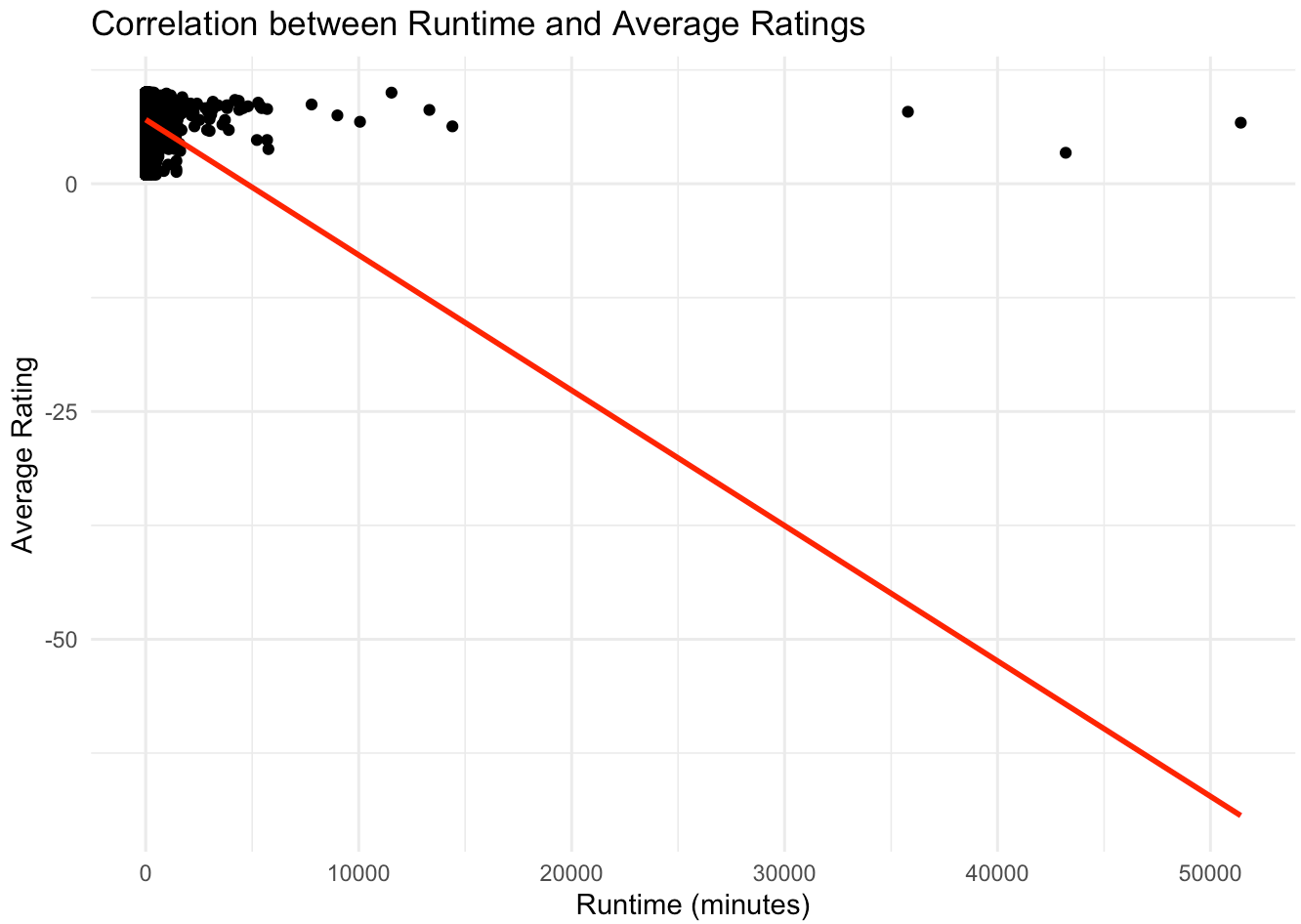
Correlation between runtime and average ratings

```
# Calculate correlation between runtime and average ratings
correlation <- cor(final_dataset$runtimeMinutes, final_dataset$averageRating)

# Print correlation
print(correlation)
```

```
## [1] -0.08715879
```

```
# Plot correlation graph
ggplot(final_dataset, aes(x = runtimeMinutes, y = averageRating)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Correlation between Runtime and Average Ratings",
       x = "Runtime (minutes)",
       y = "Average Rating") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



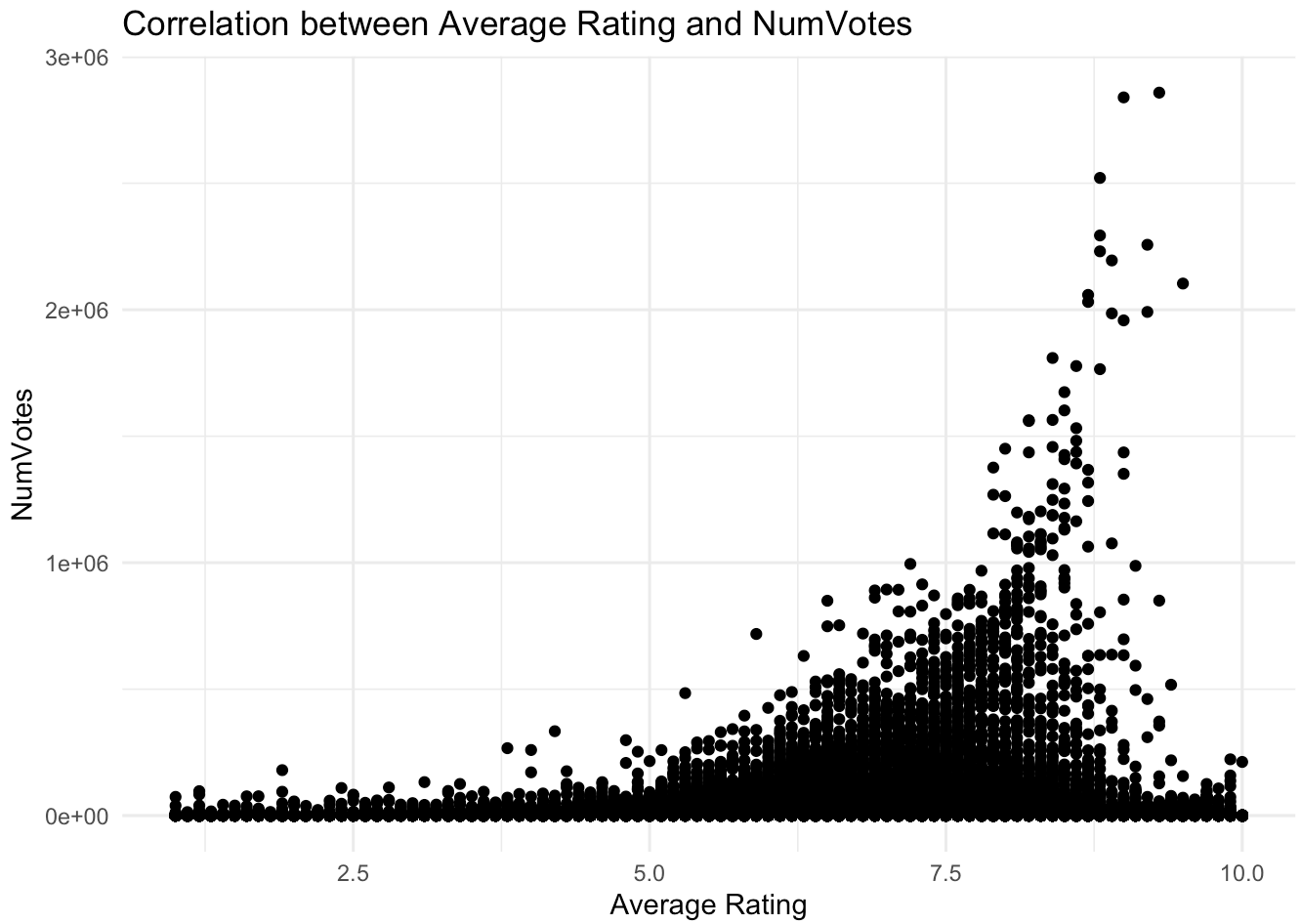
The features runtimeMinutes and averageRating are negatively corelated

Correlation between average rating and numVotes

```
# Calculate correlation between average rating and numVotes
correlation <- cor(final_dataset$averageRating, final_dataset$numVotes)

# Print correlation
print(correlation)
```

```
## [1] 0.01041723
```

```
# Plot correlation graph
ggplot(final_dataset, aes(x = averageRating, y = numVotes)) +
  geom_point() +
  labs(title = "Correlation between Average Rating and NumVotes",
       x = "Average Rating",
       y = "NumVotes") +
  theme_minimal()
```



The features numVotes and averageRating are positively corelated

Data preparation

```
head(final_dataset)
```

```
##      tconst titleType isAdult startYear runtimeMinutes
## 1 tt0000001     short       0      1894              1
## 2 tt0000002     short       0      1892              5
## 3 tt0000003     short       0      1892              4
## 4 tt0000004     short       0      1892             12
## 5 tt0000005     short       0      1893              1
## 6 tt0000006     short       0      1894              1
##                        genres averageRating numVotes
## 1         Documentary, Short           5.7     2024
## 2           Animation, Short           5.7      272
## 3 Animation, Comedy, Romance           6.5     1962
## 4           Animation, Short           5.4      178
## 5              Comedy, Short           6.2     2727
## 6                      Short           5.0      184
```

Converting all feature to integer datatype. Lets do feature encoding…

```
# Convert titleType to integer using factor
final_dataset$titleType <- as.integer(factor(final_dataset$titleType))
```

```
# Unnest the genres column to create a vector of all genres
all_genres <- unlist(final_dataset$genres)

# Get unique values of genres
unique_genres <- unique(all_genres)

# Print unique genres
print(unique_genres)
```

```
##  [1] "Documentary" "Short"       "Animation"   "Comedy"      "Romance"
##  [6] "Sport"       "News"        "Drama"       "Fantasy"     "Horror"
## [11] "Biography"   "Music"       "War"         "Crime"       "Western"
## [16] "Family"      "Adventure"   "Action"      "History"     "Mystery"
## [21] "other"       "Sci-Fi"      "Musical"     "Thriller"    "Film-Noir"
## [26] "Game-Show"   "Talk-Show"   "Reality-TV"  "Adult"
```

```
# Define a function to map genres to integers
genre_to_integer <- function(genre_list) {
  # Define a mapping of genres to integers
  genre_mapping <- c("Action" = 1, "Adventure" = 2, "Animation" = 3, "Biography" = 4,
                     "Comedy" = 5, "Crime" = 6, "Documentary" = 7, "Drama" = 8,
                     "Family" = 9, "Fantasy" = 10, "Film-Noir" = 11, "Game-Show" = 12,
                     "History" = 13, "Horror" = 14, "Music" = 15, "Musical" = 16,
                     "Mystery" = 17, "News" = 18, "Reality-TV" = 19, "Romance" = 20,
                     "Sci-Fi" = 21, "Sport" = 22, "Talk-Show" = 23, "Thriller" = 24,
                     "War" = 25, "Western" = 26, "Adult" = 27,  "Short" = 28, "other" =
29)

  # Map each genre to its corresponding integer value
  integer_list <- sapply(genre_list, function(genre) genre_mapping[genre])

  return(integer_list)
}

# Perform feature encoding on the genre feature
final_dataset$genres <- lapply(final_dataset$genre, genre_to_integer)
```

```
first_genre <- sapply(final_dataset$genre, function(x) ifelse(length(x) > 0, x[1], 29))

# Convert to factors for creating dummy variables
first_genre <- as.factor(first_genre)

temp <- final_dataset

final_dataset$genres <- as.integer(first_genre)
```

```
head(final_dataset)
```

```
##      tconst titleType isAdult startYear runtimeMinutes genres averageRating
## 1 tt0000001         2       0      1894              1      7           5.7
## 2 tt0000002         2       0      1892              5      3           5.7
## 3 tt0000003         2       0      1892              4      3           6.5
## 4 tt0000004         2       0      1892             12      3           5.4
## 5 tt0000005         2       0      1893              1      5           6.2
## 6 tt0000006         2       0      1894              1     28           5.0
##   numVotes
## 1     2024
## 2      272
## 3     1962
## 4      178
## 5     2727
## 6      184
```

```
unique_genres <- unique(final_dataset$genres)

print(unique_genres)
```

```
##  [1]  7  3  5 28 20 18  8 10 14  4 15  6  9  2  1 13 29 17 25 21 26 24 16 11 22
## [26] 12 23 27 19
```

Let's save a copy of dataset for reccomendations

```
reccon_dataset <- final_dataset
```

```
head(reccon_dataset)
```

```
##      tconst titleType isAdult startYear runtimeMinutes genres averageRating
## 1 tt0000001         2       0      1894              1      7           5.7
## 2 tt0000002         2       0      1892              5      3           5.7
## 3 tt0000003         2       0      1892              4      3           6.5
## 4 tt0000004         2       0      1892             12      3           5.4
## 5 tt0000005         2       0      1893              1      5           6.2
## 6 tt0000006         2       0      1894              1     28           5.0
##   numVotes
## 1     2024
## 2      272
## 3     1962
## 4      178
## 5     2727
## 6      184
```

Here we don't require the "tconst" feature. So lets drop it.

```
# Drop tconst column using subset()
final_dataset <- subset(final_dataset, select = -tconst)
```

```
head(final_dataset)
```

```
##   titleType isAdult startYear runtimeMinutes genres averageRating numVotes
## 1         2       0      1894              1      7           5.7     2024
## 2         2       0      1892              5      3           5.7      272
## 3         2       0      1892              4      3           6.5     1962
## 4         2       0      1892             12      3           5.4      178
## 5         2       0      1893              1      5           6.2     2727
## 6         2       0      1894              1     28           5.0      184
```

Now the data is ready for model development stage

Model development

```
# Set the seed for reproducibility
set.seed(42)

# Determine the number of rows for the training set (80%)
train_size <- 0.8

# Create an index vector for partitioning the data
train_indices <- createDataPartition(final_dataset$averageRating, p = train_size, list =
FALSE)

# Create the training and testing sets
training_data <- final_dataset[train_indices, ]
testing_data <- final_dataset[-train_indices, ]
```

```
print(nrow(training_data))
```

```
## [1] 1122989
```

```
print(nrow(testing_data))
```

```
## [1] 280747
```

```
x_train <- training_data[, !names(training_data) %in% c("averageRating")]
y_train <- training_data$averageRating

x_test <- testing_data[, !names(training_data) %in% c("averageRating")]
y_test <- testing_data$averageRating
```

```
head(x_train)
```

```
##   titleType isAdult startYear runtimeMinutes genres numVotes
## 1         2       0      1894              1      7     2024
## 2         2       0      1892              5      3      272
## 3         2       0      1892              4      3     1962
## 5         2       0      1893              1      5     2727
## 6         2       0      1894              1     28      184
## 7         2       0      1894              1     28      847
```

```
head(y_train)
```

```
## [1] 5.7 5.7 6.5 6.2 5.0 5.4
```

```
head(x_test)
```

```
##    titleType isAdult startYear runtimeMinutes genres numVotes
## 4          2       0      1892             12      3      178
## 10         2       0      1895              1      7     7449
## 17         2       0      1895              1      7      339
## 21         2       0      1895              1      7     1127
## 23         2       0      1895              1     18      126
## 43         2       0      1896              1     28       49
```

```
head(y_test)
```

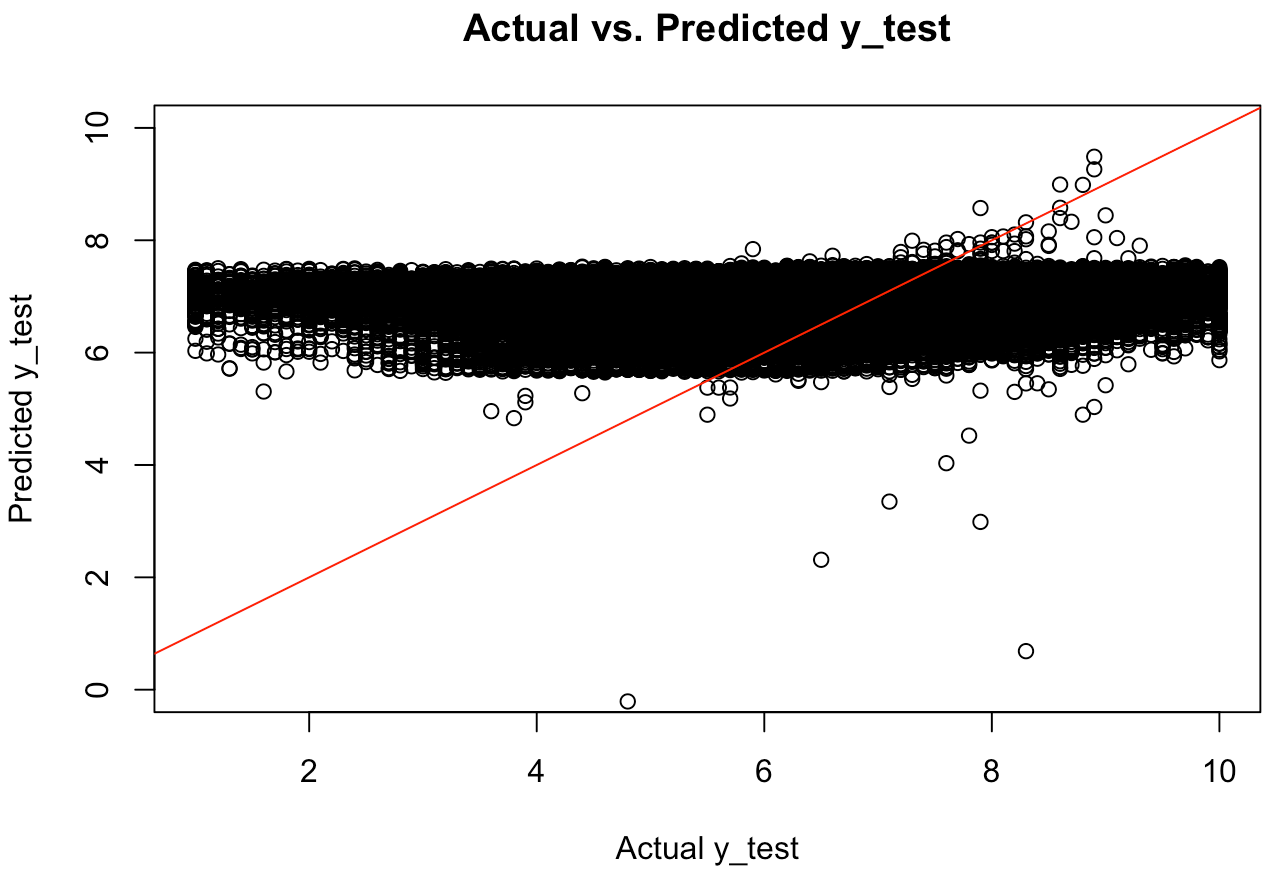
```
## [1] 5.4 6.8 4.6 5.1 3.9 4.0
```

Linear regression model

```
# Build the multiple linear regression model using training data
lm_model <- lm(averageRating ~ ., data = training_data)
```

```
# Predict y values using the model
lm_y_pred <- predict(lm_model, newdata = testing_data)
```

```
plot(y_test, lm_y_pred,
     xlab = "Actual y_test", ylab = "Predicted y_test",
     main = "Actual vs. Predicted y_test",
     ylim = c(0, 10))
abline(0, 1, col = "red")
```




```
summary(lm_model)
```

```
##
## Call:
## lm(formula = averageRating ~ ., data = training_data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.496 -0.714  0.177  0.898 68.531
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -1.269e+01  1.214e-01 -104.49   <2e-16 ***
## titleType       5.141e-02  6.788e-04   75.73   <2e-16 ***
## isAdult        -7.939e-01  1.103e-02  -71.95   <2e-16 ***
## startYear       9.778e-03  6.074e-05  160.99   <2e-16 ***
## runtimeMinutes -1.339e-03  1.578e-05  -84.86   <2e-16 ***
## genres         -2.208e-03  1.581e-04  -13.96   <2e-16 ***
## numVotes        1.295e-06  7.266e-08   17.82   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.357 on 1122982 degrees of freedom
## Multiple R-squared:  0.04205,    Adjusted R-squared:  0.04204
## F-statistic:  8215 on 6 and 1122982 DF,  p-value: < 2.2e-16
```

```
# Calculate Mean Absolute Error (MAE)
MAE <- mean(abs(lm_y_pred - y_test))
cat("Mean Absolute Error (MAE):", MAE, "\n")
```

```
## Mean Absolute Error (MAE): 1.029465
```

```
# Calculate Mean Squared Error (MSE)
MSE <- mean((lm_y_pred - y_test)^2)
cat("Mean Squared Error (MSE):", MSE, "\n")
```

```
## Mean Squared Error (MSE): 1.82996
```

```
# Calculate Root Mean Squared Error (RMSE)
RMSE <- sqrt(MSE)
cat("Root Mean Squared Error (RMSE):", RMSE, "\n")
```

```
## Root Mean Squared Error (RMSE): 1.35276
```

```
# Calculate R-squared
SS_res <- sum((lm_y_pred - y_test)^2)
SS_tot <- sum((y_test - mean(y_test))^2)
R_squared <- 1 - (SS_res / SS_tot)
cat("R-squared:", R_squared, "\n")
```

```
## R-squared: 0.04318821
```

KNN regression model

```
# Build the KNN model using training data
knn_final_model <- knn.reg(train = x_train, test = x_test, y = y_train, k = 10)  # Adjus
t the value of k as needed
```

```
# Predict average ratings for testing data
knn_pred_ratings <- knn_final_model$pred

# Print the predicted ratings
head(knn_pred_ratings)
```

```
## [1] 4.98 7.38 5.34 5.78 4.85 4.99
```

```
# Calculate Mean Absolute Error (MAE)
MAE <- mean(abs(knn_pred_ratings - y_test))
cat("Mean Absolute Error (MAE):", MAE, "\n")
```

```
## Mean Absolute Error (MAE): 0.9068456
```

```
# Calculate Mean Squared Error (MSE)
MSE <- mean((knn_pred_ratings - y_test)^2)
cat("Mean Squared Error (MSE):", MSE, "\n")
```

```
## Mean Squared Error (MSE): 1.509794
```

```
# Calculate Root Mean Squared Error (RMSE)
RMSE <- sqrt(MSE)
cat("Root Mean Squared Error (RMSE):", RMSE, "\n")
```

```
## Root Mean Squared Error (RMSE): 1.228737
```

```
# Calculate R-squared
SS_res <- sum((knn_pred_ratings - y_test)^2)
SS_tot <- sum((y_test - mean(y_test))^2)
R_squared <- 1 - (SS_res / SS_tot)
cat("R-squared:", R_squared, "\n")
```

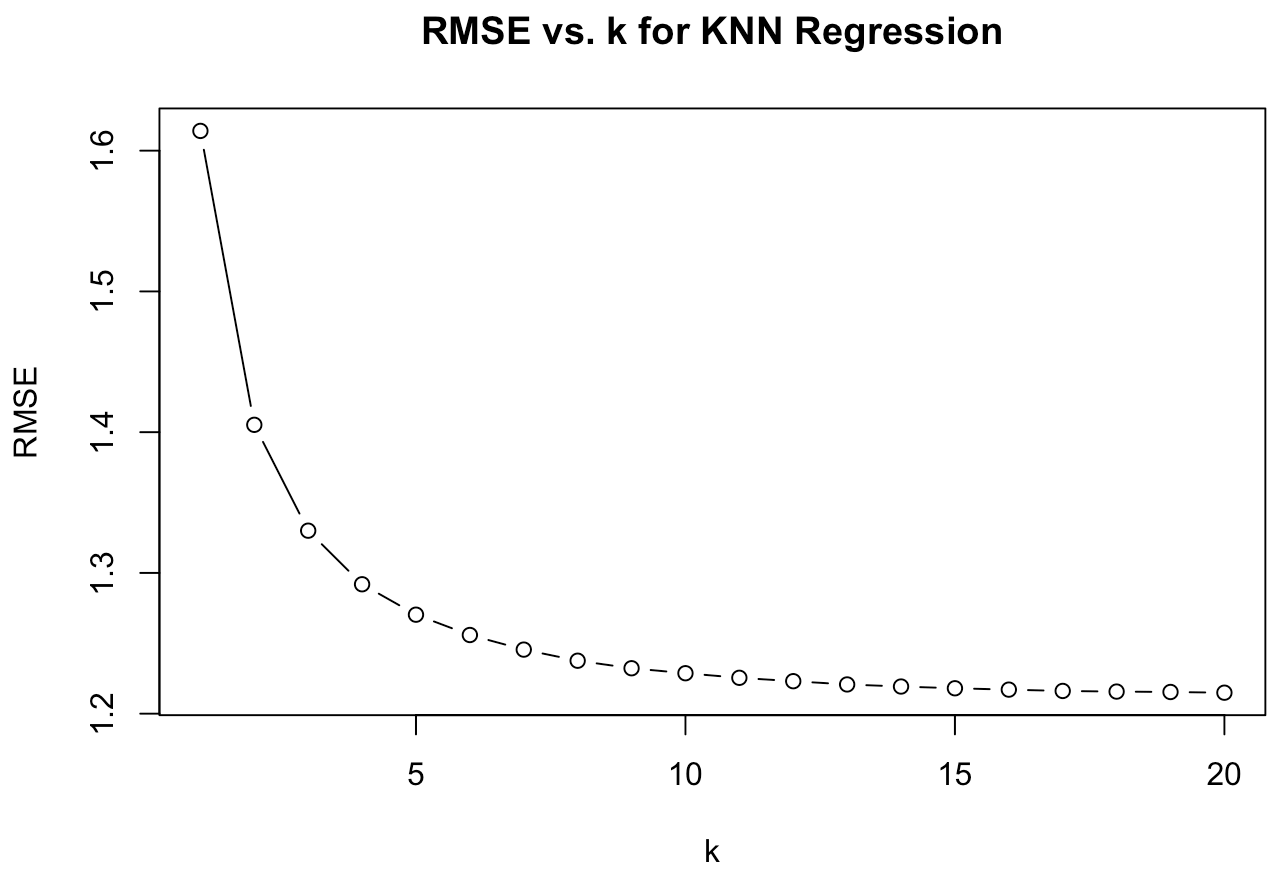
```
## R-squared: 0.2105901
```

```
# Define a function to calculate RMSE for KNN regression
knn_rmse <- function(k, train_data, test_data) {

  # Train KNN regression model
  knn_model <- knn.reg(train = x_train, test = x_test, y = y_train, k = k)

  # Predict on test data
  predictions <- knn_model$pred

  cat("For the k = ", k, "\n")
  # Calculate Root Mean Squared Error (RMSE)
  RMSE <- sqrt(mean((predictions - y_test)^2))
  cat("Root Mean Squared Error (RMSE):", RMSE, "\n")
  print("-------------------------------------")

  return(RMSE)
}


# Perform grid search to find the best k value
k_values <- 1:20
rmse_values <- sapply(k_values, function(k) knn_rmse(k, training_data, testing_data))
```

```
## For the k =  1
## Root Mean Squared Error (RMSE): 1.614034
## [1] "-----------------------------------"
## For the k =  2
## Root Mean Squared Error (RMSE): 1.405222
## [1] "-----------------------------------"
## For the k =  3
## Root Mean Squared Error (RMSE): 1.330015
## [1] "-----------------------------------"
## For the k =  4
## Root Mean Squared Error (RMSE): 1.291941
## [1] "-----------------------------------"
## For the k =  5
## Root Mean Squared Error (RMSE): 1.270332
## [1] "-----------------------------------"
## For the k =  6
## Root Mean Squared Error (RMSE): 1.255893
## [1] "-----------------------------------"
## For the k =  7
## Root Mean Squared Error (RMSE): 1.245517
## [1] "-----------------------------------"
## For the k =  8
## Root Mean Squared Error (RMSE): 1.237622
## [1] "-----------------------------------"
## For the k =  9
## Root Mean Squared Error (RMSE): 1.232273
## [1] "-----------------------------------"
## For the k =  10
## Root Mean Squared Error (RMSE): 1.228737
## [1] "-----------------------------------"
## For the k =  11
## Root Mean Squared Error (RMSE): 1.225487
## [1] "-----------------------------------"
## For the k =  12
## Root Mean Squared Error (RMSE): 1.223079
## [1] "-----------------------------------"
## For the k =  13
## Root Mean Squared Error (RMSE): 1.220765
## [1] "-----------------------------------"
## For the k =  14
## Root Mean Squared Error (RMSE): 1.21929
## [1] "-----------------------------------"
## For the k =  15
## Root Mean Squared Error (RMSE): 1.218051
## [1] "-----------------------------------"
## For the k =  16
## Root Mean Squared Error (RMSE): 1.217086
## [1] "-----------------------------------"
## For the k =  17
## Root Mean Squared Error (RMSE): 1.216145
## [1] "-----------------------------------"
## For the k =  18
```

```
## Root Mean Squared Error (RMSE): 1.215699
## [1] "-----------------------------------"
## For the k =  19
## Root Mean Squared Error (RMSE): 1.215407
## [1] "-----------------------------------"
## For the k =  20
## Root Mean Squared Error (RMSE): 1.214908
## [1] "-----------------------------------"
```

```
# Plot RMSE values for different k values
plot(k_values, rmse_values, type = "b", xlab = "k", ylab = "RMSE", main = "RMSE vs. k fo
r KNN Regression")
```



Selecting an optimal value for k in KNN is crucial for achieving the right balance between bias and variance. Lower values of k may lead to overfitting, capturing noise in the data, while higher values of k may result in underfitting, oversimplifying the model. After evaluating the model's performance for various k values, we observed that the RMSE values plateaued after k = 10. This indicates that increasing the value of k beyond 10 does not significantly improve the model's performance. It suggests that the model starts to overfit the data beyond k = 10. Therefore, based on this analysis, we have chosen k = 10 as the optimal value for our KNN model. This value strikes a balance between capturing the underlying patterns in the data and avoiding overfitting.

Decision Tree

```
# Build the decision tree model using training data
tree_model <- rpart(formula = y_train ~ ., data = x_train)
```

```
# Predict average ratings for testing data
tree_pred_ratings <- predict(tree_model, newdata = x_test)

# Print the predicted ratings
head(tree_pred_ratings)
```

```
##        4       10       17       21       23       43
## 5.726709 5.726709 5.726709 5.726709 5.726709 5.726709
```

```
summary(tree_model)
```

```
## Call:
## rpart(formula = y_train ~ ., data = x_train)
##   n= 1122989
##
##           CP nsplit rel error    xerror        xstd
## 1 0.08852954      0 1.0000000 1.0000036 0.001672212
## 2 0.02154786      1 0.9114705 0.9114745 0.001634130
## 3 0.01926800      2 0.8899226 0.8899275 0.001592392
## 4 0.01000000      3 0.8706546 0.8706605 0.001586000
##
## Variable importance
##      titleType runtimeMinutes      startYear       numVotes        isAdult
##             59             28             11              1              1
##
## Node number 1: 1122989 observations,    complexity param=0.08852954
##   mean=6.955654, MSE=1.922095
##   left son=2 (243631 obs) right son=3 (879358 obs)
##   Primary splits:
##       titleType      < 1.5    to the left,  improve=0.088529540, (0 missing)
##       runtimeMinutes < 62.5   to the right, improve=0.088311050, (0 missing)
##       startYear      < 1951.5 to the left,  improve=0.018360130, (0 missing)
##       numVotes       < 13.5   to the right, improve=0.005344171, (0 missing)
##       genres         < 7.5    to the right, improve=0.004320781, (0 missing)
##   Surrogate splits:
##       runtimeMinutes < 72.5   to the right, agree=0.894, adj=0.510, (0 split)
##       numVotes       < 5170.5 to the right, agree=0.789, adj=0.028, (0 split)
##       startYear      < 1951.5 to the left,  agree=0.786, adj=0.013, (0 split)
##
## Node number 2: 243631 observations
##   mean=6.171957, MSE=1.890874
##
## Node number 3: 879358 observations,    complexity param=0.02154786
##   mean=7.172781, MSE=1.713439
##   left son=6 (182658 obs) right son=7 (696700 obs)
##   Primary splits:
##       titleType      < 4.5    to the right, improve=0.030868840, (0 missing)
##       startYear      < 1949.5 to the left,  improve=0.023493090, (0 missing)
##       runtimeMinutes < 66.5   to the right, improve=0.018464580, (0 missing)
##       isAdult        < 0.5    to the right, improve=0.005183296, (0 missing)
##       numVotes       < 529.5  to the left,  improve=0.005126594, (0 missing)
##   Surrogate splits:
##       runtimeMinutes < 47.5   to the right, agree=0.858, adj=0.316, (0 split)
##       isAdult        < 0.5    to the right, agree=0.806, adj=0.068, (0 split)
##       numVotes       < 8273.5 to the right, agree=0.793, adj=0.004, (0 split)
##
## Node number 6: 182658 observations
##   mean=6.723624, MSE=2.161057
##
## Node number 7: 696700 observations,    complexity param=0.019268
##   mean=7.290539, MSE=1.529325
##   left son=14 (16601 obs) right son=15 (680099 obs)
##   Primary splits:
```

```
##       startYear      < 1950.5 to the left,  improve=0.039033850, (0 missing)
##       titleType      < 2.5    to the left,  improve=0.029819600, (0 missing)
##       runtimeMinutes < 18.5   to the left,  improve=0.026089870, (0 missing)
##       numVotes       < 287.5  to the left,  improve=0.012490180, (0 missing)
##       genres         < 8.5    to the right, improve=0.002029804, (0 missing)
##
## Node number 14: 16601 observations
##   mean=5.726709, MSE=1.457866
##
## Node number 15: 680099 observations
##   mean=7.328712, MSE=1.469917
```

```
# Calculate Mean Absolute Error (MAE)
MAE <- mean(abs(tree_pred_ratings - y_test))
cat("Mean Absolute Error (MAE):", MAE, "\n")
```

```
## Mean Absolute Error (MAE): 0.9740413
```

```
# Calculate Mean Squared Error (MSE)
MSE <- mean((tree_pred_ratings - y_test)^2)
cat("Mean Squared Error (MSE):", MSE, "\n")
```

```
## Mean Squared Error (MSE): 1.665022
```

```
# Calculate Root Mean Squared Error (RMSE)
RMSE <- sqrt(MSE)
cat("Root Mean Squared Error (RMSE):", RMSE, "\n")
```

```
## Root Mean Squared Error (RMSE): 1.290357
```

```
# Calculate R-squared
SS_res <- sum((tree_pred_ratings - y_test)^2)
SS_tot <- sum((y_test - mean(y_test))^2)
R_squared <- 1 - (SS_res / SS_tot)
cat("R-squared:", R_squared, "\n")
```

```
## R-squared: 0.1294278
```

Based on these metrics, the KNN Regression Model appears to perform the best among the three models.

Reccomendations - Top 10 Reccomended movies

Let's apply the KNN regression model on total dataset and predit the ratings. Based on these ratings, reccommend the top rated movies

```
# Join reccon_dataset and movie_dataset using tconst as the key to get the originalTitle feature from movie_dataset
merged_dataset <- merge(reccon_dataset, movies_dataset[, c("tconst", "originalTitle")], by = "tconst", all.x = TRUE)
#Considering whole dataset as a testing dataset
new_test_dataset <- subset(merged_dataset, select = c(titleType, isAdult,startYear, runtimeMinutes, genres, numVotes))


# Building knn regression model
knn_recc_model <- knn.reg(train = x_train, test = new_test_dataset, y = y_train, k = 10)
# Predict average ratings for testing data
knn_recc_predratings <- knn_recc_model$pred


# Attach predicted ratings to the dataset
merged_dataset$predicted_ratings <- knn_recc_predratings
# Sort entries by predicted_ratings in descending order
merged_dataset <- merged_dataset[order(merged_dataset$predicted_ratings, decreasing = TRUE), ]
print(merged_dataset[1:10, c("originalTitle", "predicted_ratings")])
```

```
##                                                                 originalTitle
## 283831                                                   Along for the Ride
## 321748                                                    The Art of Biting
## 351916                                                  Comenzando De Nuevo
## 351917                                                             El Baile
## 391103                                                          Jalkapuussa
## 547198                                                              Bolum 1
## 558662                                          Fear and Falling in Montana
## 558664                                                    Making Allowances
## 558666                                                         Solar Mates
## 567757 Jennifer's Instinct; Sailors Angel; OR Miracle; High School Reunion
##        predicted_ratings
## 283831                10
## 321748                10
## 351916                10
## 351917                10
## 391103                10
## 547198                10
## 558662                10
## 558664                10
## 558666                10
## 567757                10
```

Here are the top 10 reccomended movie by the KNN regression model.