RMarkdown

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INTRODUCTION

This document provides a detailed report of our data exploration where we focus on exploring the raw data before any cleaning or modeling occurs, including: - How the datasets were loaded - Data quality observations: missing values and outliers - An overview of the structure and the relevant variables

RESEARCH QUESTION

How does runtime influence audience ratings for movies compared to TV episodes, controlling for the release year?

RESEARCH METHOD

By conducting a multiple linear regression, we will estimate the independent effect of runtime on ratings while controlling for release year and content type (movie/TV episode).

DEPENDENCIES

For the data exploration step, we used the following dependencies: - R - Make - Installed packages in R:

```r
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.2
## v ggplot2   4.0.0     v tibble    3.3.0
## v lubridate 1.9.4     v tidyr     1.3.1
## v purrr     1.1.0
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become error
```

```r
library(ggplot2)
library(data.table)
```

```
##
## Attaching package: 'data.table'
##
## The following objects are masked from 'package:lubridate':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday, week,
##     yday, year
##
## The following objects are masked from 'package:dplyr':
##
##     between, first, last
##
## The following object is masked from 'package:purrr':
##
##     transpose
```

LOADING THE DATASETS

Two separate datasets were acquired from IMDb (https://datasets.imdbws.com/): - The first dataset contains information on the contents' duration and release year, saved as "title_basics_raw" - The second dataset contains information on the contents' ratings, saved as "ratings_raw"

The following chunk of code will first create the folder "raw" to store the raw datasets, and second, load the datasets into R:

```r
# Ensure the "raw" folder exists
dir.create("raw", recursive = TRUE, showWarnings = FALSE)

# Retrieve dataset for Movie and TV Episode Duration and Release Year
title_url <- "https://datasets.imdbws.com/title.basics.tsv.gz"
title_basics_raw <- read_tsv(title_url, na = c("\\N", ""))
```

```
## Warning: One or more parsing issues, call `problems()` on your data frame for details,
## e.g.:
##   dat <- vroom(...)
##   problems(dat)
```

```
## Rows: 11957318 Columns: 9
## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## chr (5): tconst, titleType, primaryTitle, originalTitle, genres
## dbl (4): isAdult, startYear, endYear, runtimeMinutes
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
# Retrieve dataset for rating
rating_url <- "https://datasets.imdbws.com/title.ratings.tsv.gz"
ratings_raw <- read_tsv(rating_url, na = c("\\N", ""))
```

```
## Rows: 1623466 Columns: 3
## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## chr (1): tconst
## dbl (2): averageRating, numVotes
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
# Save the downloaded datasets to folder "raw"
write_tsv(title_basics_raw, "raw/title_basics_raw.tsv")
write_tsv(ratings_raw, "raw/ratings_raw.tsv")
```

DATA QUALITY OBSERVATIONS

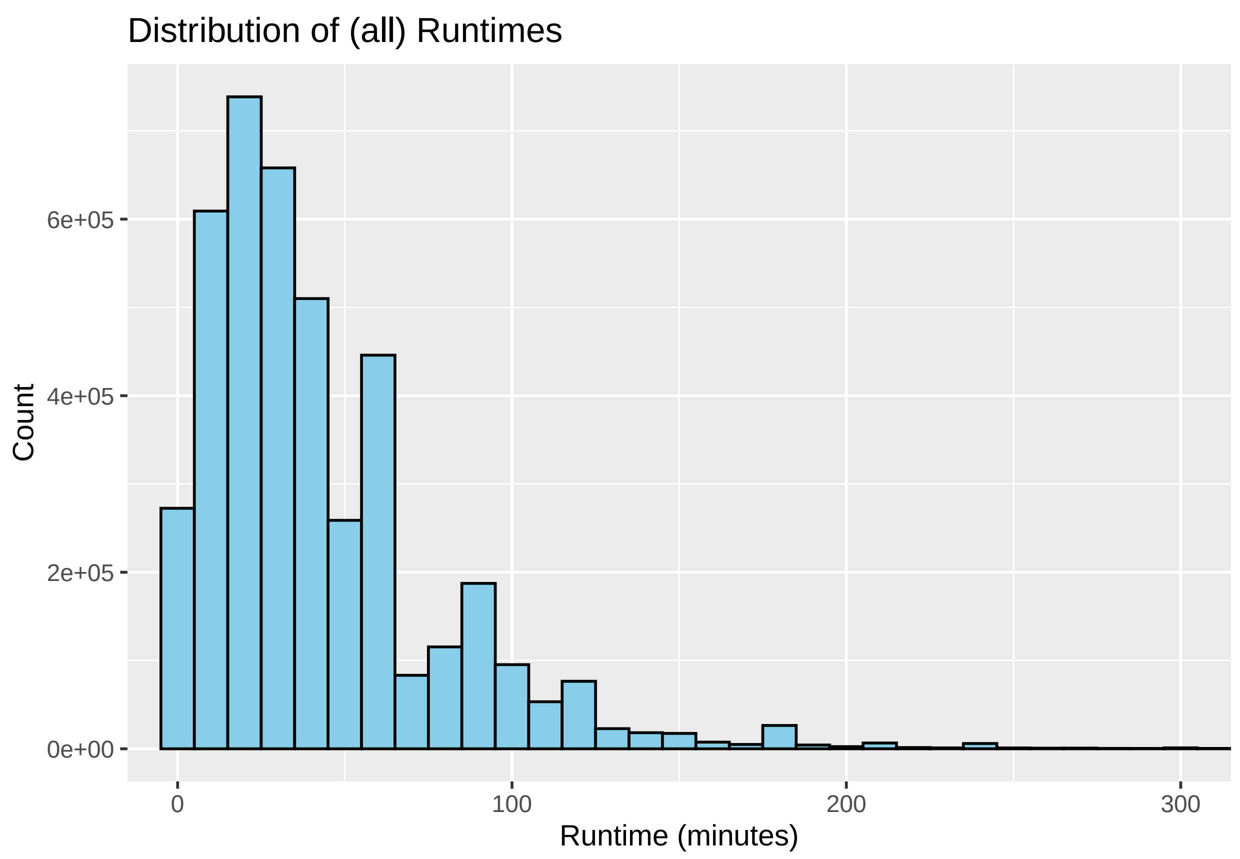
The following chunk of code provides a data quality check to identify missing values and outliers:

```r
# Data quality check for title_basics_raw
  # Missing values
colSums(is.na(title_basics_raw[c("tconst", "primaryTitle", "startYear", "runtimeMinutes")]))
```

```
##         tconst   primaryTitle      startYear runtimeMinutes
##              0              0        1441269        7723555
```

```r
  # Outliers
setDT(title_basics_raw)
ggplot(title_basics_raw, aes(x = runtimeMinutes)) +
  geom_histogram(binwidth = 10, fill = "skyblue", color = "black") +
  coord_cartesian(xlim = c(0, 300)) +  # focus on typical runtimes
  labs(x = "Runtime (minutes)", y = "Count", title = "Distribution of (all) Runtimes")
```

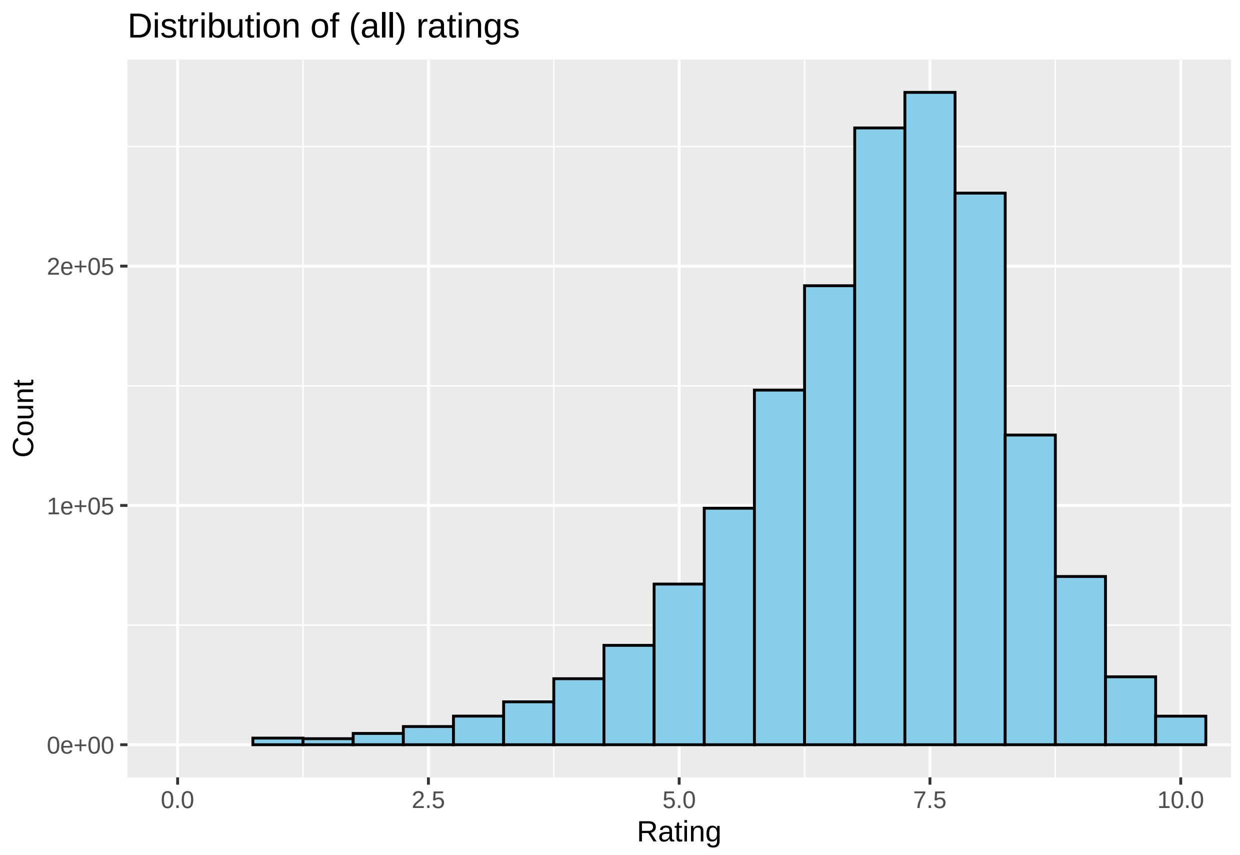
```
## Warning: Removed 7723555 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



```r
# Data quality check for title_ratings
  # Missing values
colSums(is.na(ratings_raw[c("tconst","averageRating")]))
```

```
##        tconst averageRating
##             0             0
```

```r
  # Outliers
setDT(ratings_raw)
ggplot(ratings_raw, aes(x = averageRating)) +
  geom_histogram(binwidth = 0.5, fill = "skyblue", color = "black") +
  coord_cartesian(xlim = c(0, 10)) +
  labs(x = "Rating", y = "Count", title = "Distribution of (all) ratings")
```



OVERVIEW OF THE STRUCTURE AND RELEVANT VARIABLES

Below you will find the variable names and descriptions that are relevant to this study. 1. tconst(string): alphanumeric unique identifier of the title 2. primaryTitle (string):the more popular title/the title used by the filmmakers on promotional materials at the point of release 3. startYear: represents the release year of a title 4. runtimeMinutes: primary runtime of the title, in minutes 5. averageRating: weighted average of all the individual user ratings 6. is_tvepisode (boolean): 0: content type is Movie, 1: content type is TV Episode

DATA CLEANING

The following chunk of code will first create the folder “tmp” to store the tmp datasets, and second, filter only on movies and TVepisodes.

```r
# Ensure the "tmp" folder exists
dir.create("tmp", recursive = TRUE, showWarnings = FALSE)

# Both \N and empty strings to be treated as NAs
title_basics_raw <- read_tsv("raw/title_basics_raw.tsv", na = c("\\N", ""), show_col_types = FALSE)
```

```
## Warning: One or more parsing issues, call ‘problems()‘ on your data frame for details,
## e.g.:
##   dat <- vroom(...)
##   problems(dat)
```

```r
# Filter only movies and TVepisodes > save in tmp
filtered_movies_TVepisodes <- title_basics_raw %>%
  filter(titleType %in% c("movie", "tvEpisode"))

# Output cleanded data
write_tsv(filtered_movies_TVepisodes, "tmp/filtered_movies_TVepisodes.tsv")
```

DATA MERGING

The following chunk of code will merge the datasets and make a dummy variable.

```r
# Merge with ratings
merged_data <- filtered_movies_TVepisodes %>%
  left_join(ratings_raw, by = "tconst")

cat("Number of unmatched rows:", sum(is.na(merged_data$averageRating)), "\n")
```

```
## Number of unmatched rows: 8767902
```

```r
#  Create dummy variable for TVepisodes > save in tmp
merged_data <- merged_data %>%
  mutate(is_tvepisode = ifelse(titleType == "tvEpisode", 1,0))

# Output merged_data
write_tsv(merged_data, "tmp/merged_data.tsv")
```

DATA FINAL CLEANING

The following chunk of code will provide the final cleaning. This includes selecting revelant columns, removing missing values, creating the gen folder and removing the extreme outliers.

```r
# Select relevant columns, remove missing values, de-duplicate > save in gen
analysis_data <- fread("tmp/merged_data.tsv")
```

```
## Warning in fread("tmp/merged_data.tsv"): Stopped early on line 776998. Expected
## 12 fields but found 13. Consider fill=TRUE and comment.char=. First discarded
## non-empty line: <<tt10233364 tvEpisode Rolling in the Deep Dish Rolling in the
## Deep Dish 0 2019 NA NA NA NA NA NA 1>>
```

```r
analysis_data[, c("originalTitle", "titleType", "isAdult", "endYear", "genres", "numVotes") := NULL]
analysis_data <- analysis_data[!is.na(runtimeMinutes) & !is.na(averageRating)& !is.na(startYear)] %>% d

write_tsv(analysis_data, "tmp/analysis_data.tsv")
```

```r
# Create gen folder for analysis_data_clean
dir.create("gen", recursive = TRUE, showWarnings = FALSE)

# Remove extreme outliers for runtime
analysis_data_clean <- analysis_data %>%
  group_by(is_tvepisode) %>%
  filter({
    Q1 <- quantile(runtimeMinutes, 0.25)
    Q3 <- quantile(runtimeMinutes, 0.75)
    IQR_val <- Q3 - Q1
    runtimeMinutes >= (Q1 - 1.5 * IQR_val) & runtimeMinutes <= (Q3 + 1.5 * IQR_val)
  }) %>%
  ungroup()

# Remove extreme outliers for runtime TVepisodes
analysis_data_clean %>%
  filter(runtimeMinutes < 15, is_tvepisode==1) %>%
  summarise(count = n())
```

```
## # A tibble: 1 x 1
##   count
##   <int>
## 1  1710
```

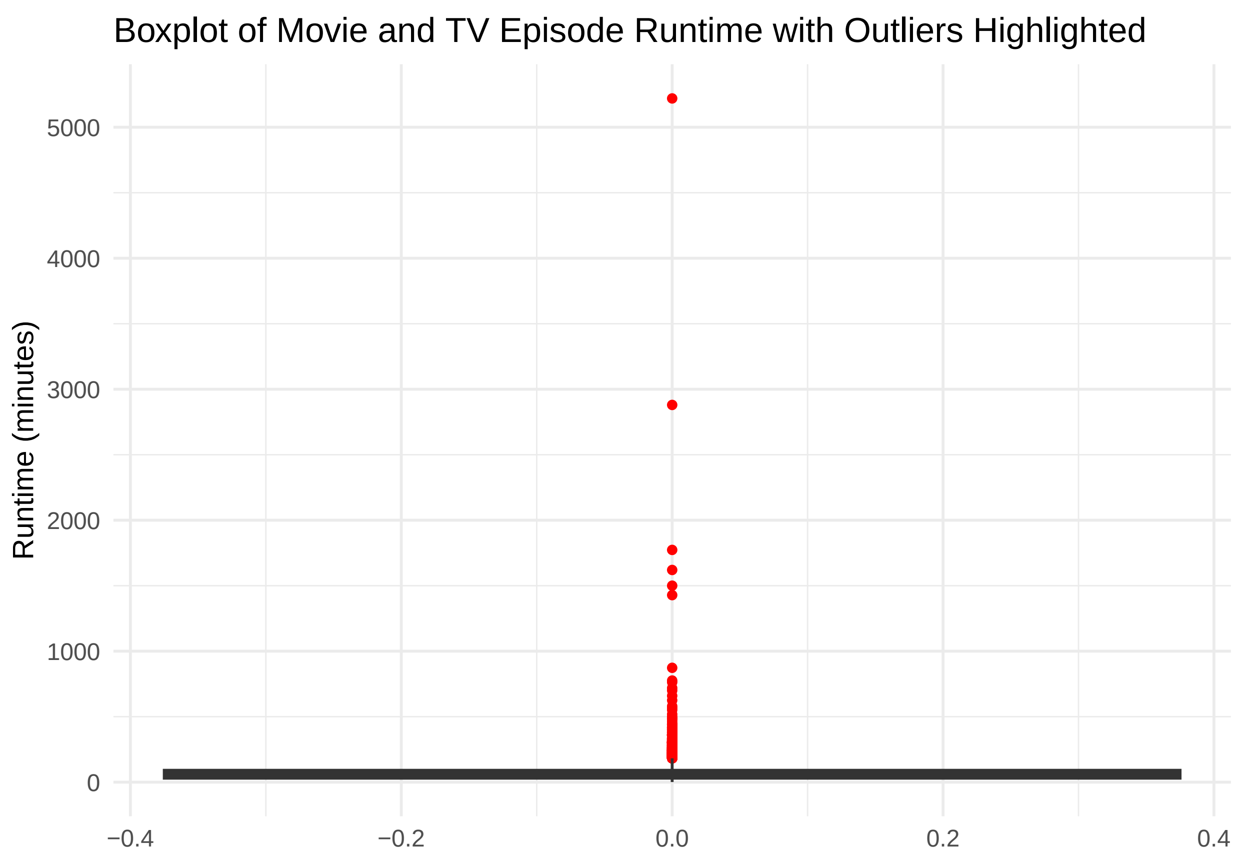
```r
## Removing TV episodes that are shorter than 15 minutes or longer than 65 minutes
analysis_data_clean <- analysis_data_clean %>%
  filter(is_tvepisode != 1 | (runtimeMinutes >= 15 & runtimeMinutes <= 65))

# Output final cleaned data
write_tsv(analysis_data_clean, "gen/analysis_data_clean.tsv")
```

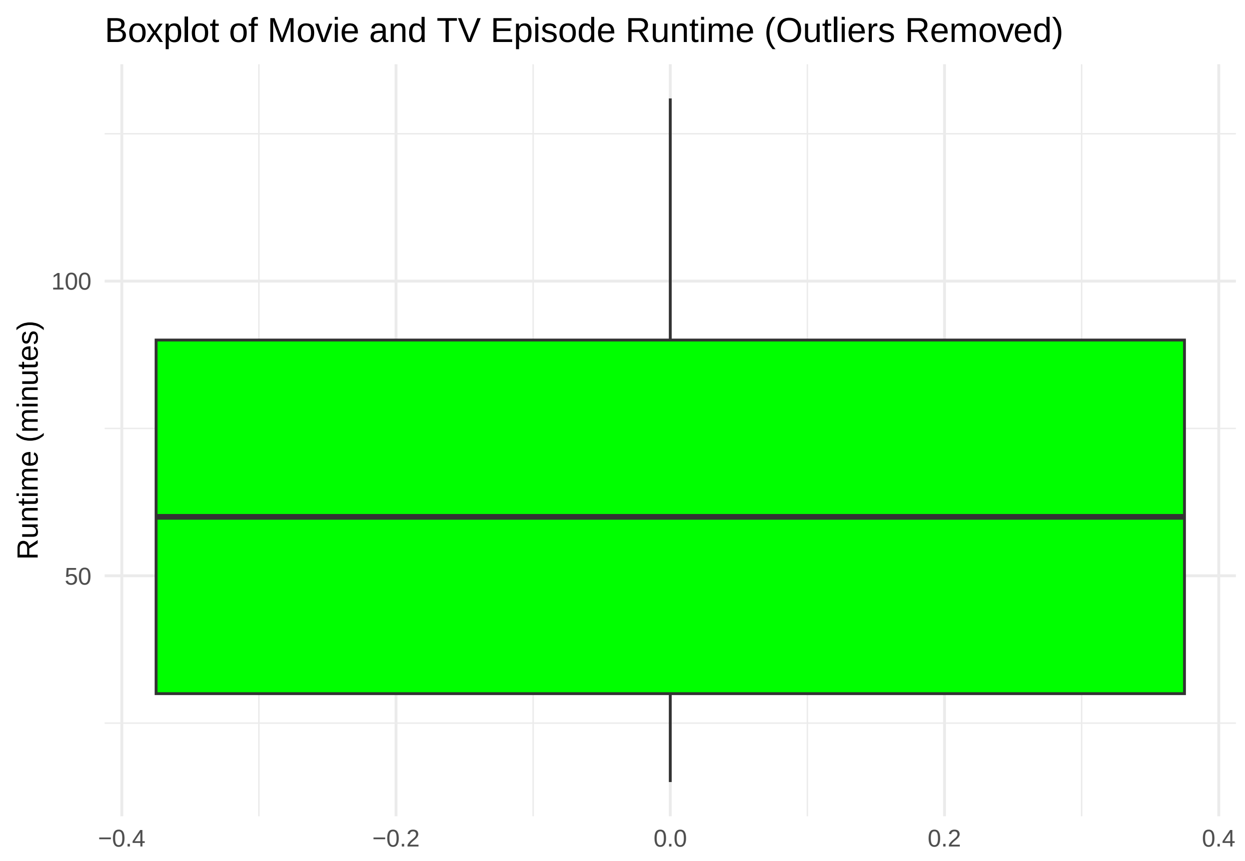
INCLUDING PLOTS

The following chunk of code will provide the boxplots that are used for the final cleaning of the data.

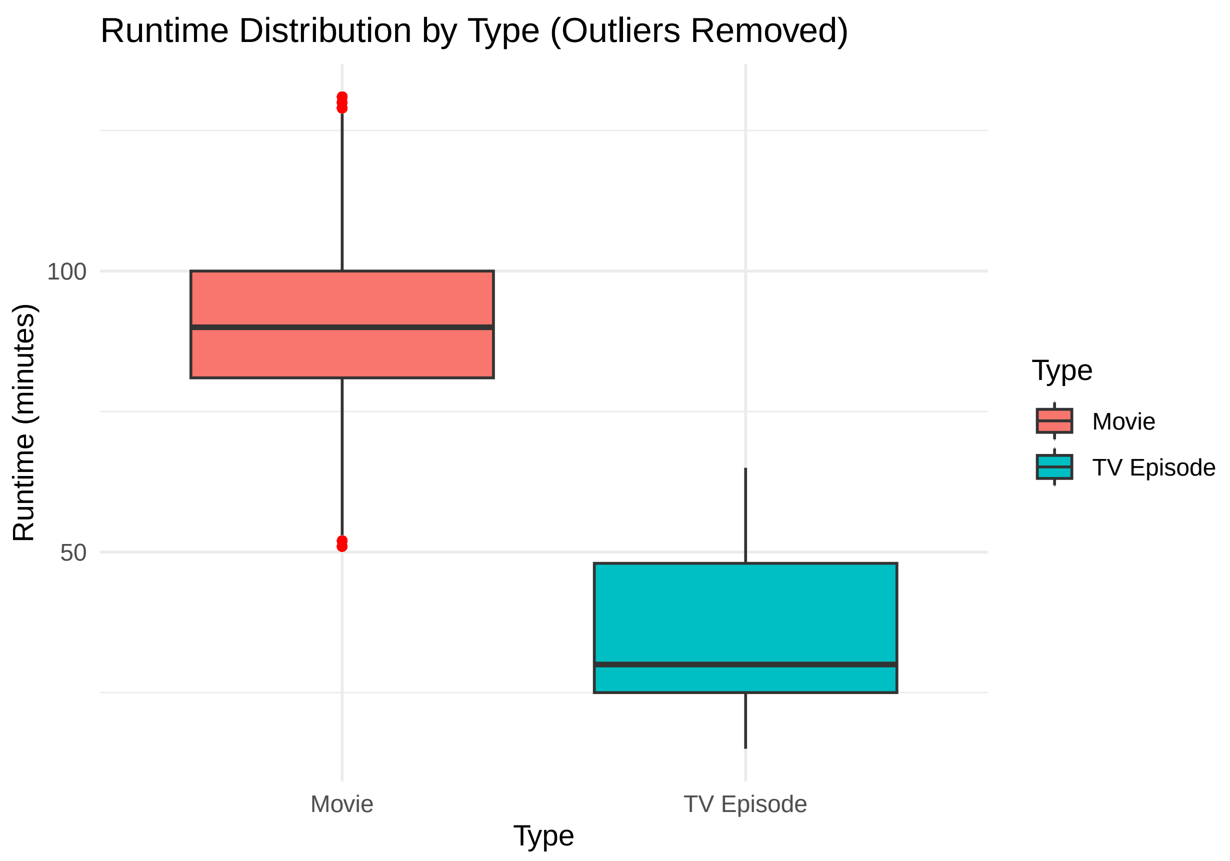
```r
# Analyzing the date through a plot
ggplot(analysis_data, aes(y = runtimeMinutes)) +
  geom_boxplot(fill = "blue", outlier.color = "red", outlier.shape = 16) +
  labs(
    y = "Runtime (minutes)",
    title = "Boxplot of Movie and TV Episode Runtime with Outliers Highlighted"
  ) +
  theme_minimal()
```



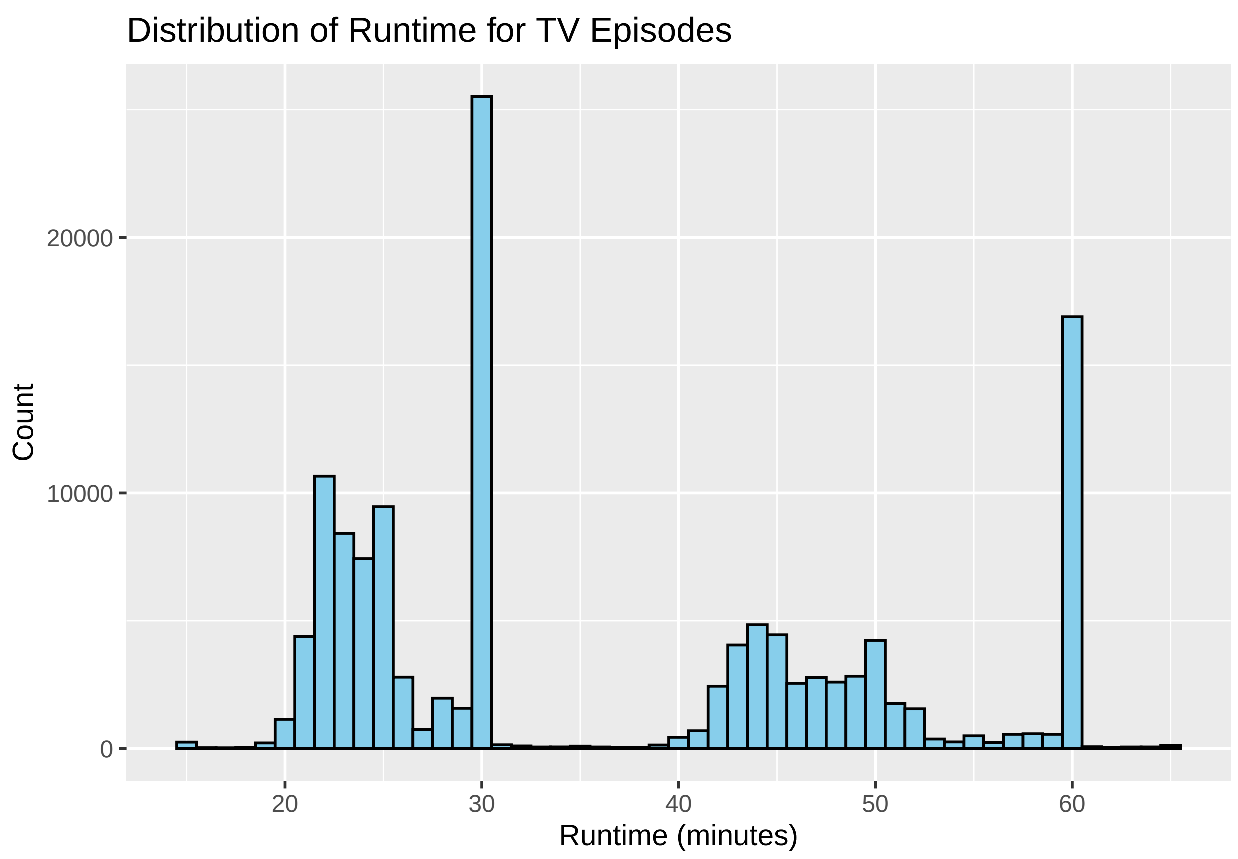
```r
# Boxplot with outliers Removed
ggplot(analysis_data_clean, aes(y = runtimeMinutes)) +
  geom_boxplot(fill = "green") +
  labs(
    y = "Runtime (minutes)",
    title = "Boxplot of Movie and TV Episode Runtime (Outliers Removed)"
  ) +
  theme_minimal()
```



```r
# Plot after removing outliers per group
ggplot(analysis_data_clean, aes(x = factor(is_tvepisode, labels = c("Movie", "TV Episode")),
                                y = runtimeMinutes,
                                fill = factor(is_tvepisode, labels = c("Movie", "TV Episode")))) +
  geom_boxplot(outlier.color = "red", outlier.shape = 16) +
  labs(
    x = "Type",
    y = "Runtime (minutes)",
    fill = "Type",
    title = "Runtime Distribution by Type (Outliers Removed)"
  ) +
  theme_minimal()
```



```r
# Analysing the data through a plot
analysis_data_clean %>%
  filter(is_tvepisode == 1) %>%
  ggplot(aes(x = runtimeMinutes)) +
  geom_histogram(binwidth = 1, fill = "skyblue", color = "black") +
  labs(title = "Distribution of Runtime for TV Episodes",
       x = "Runtime (minutes)",
       y = "Count")
```



REGRESSION ANALYSIS

The following chunk of code will provide the regression analysis.

```r
# Change runtimeMinutes to mean
analysis_data_clean <- analysis_data_clean %>%
  mutate(mruntimeMinutes = runtimeMinutes - mean(runtimeMinutes, na.rm = TRUE))

# Change baseline to 1896
analysis_data_clean <- analysis_data_clean %>%
  mutate(startYearCentered = startYear - 1896)

# Regression with interaction effect controlling for release year
model_1 <- lm(averageRating ~ mruntimeMinutes * is_tvepisode + startYearCentered, data = analysis_data_c
summary(model_1)
```

```
##
## Call:
## lm(formula = averageRating ~ mruntimeMinutes * is_tvepisode +
##     startYearCentered, data = analysis_data_clean)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.4982 -0.5317  0.1040  0.6401  4.1068
```

```
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 5.9103738  0.0090194  655.29   <2e-16 ***
## mruntimeMinutes             0.0076482  0.0001875   40.79   <2e-16 ***
## is_tvepisode                1.6960140  0.0086734  195.54   <2e-16 ***
## startYearCentered          -0.0016597  0.0001012  -16.40   <2e-16 ***
## mruntimeMinutes:is_tvepisode -0.0043764  0.0002832  -15.46   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.028 on 260460 degrees of freedom
## Multiple R-squared:  0.3158, Adjusted R-squared:  0.3158
## F-statistic: 3.006e+04 on 4 and 260460 DF,  p-value: < 2.2e-16
```

THEORETICAL IMPLICATIONS

This study contributes to academic understanding by examining how runtime shapes audience ratings across different formats such as movies and TV episodes. The findings reveal that there is a positive relationship between runtime and audience ratings, with longer runtimes being more beneficial for movies than for TV episodes.

This aligns with existing theories of immersive engagement, which show that longer content enables more complex storytelling and viewers being fully engaged in the story, which result in a better overall viewer experience and evaluation. The weaker effect of duration on ratings for TV episodes compared to movies may be caused by different aspects, such as the story building up over many shorter parts. Further research should take into account how different media formats affect how people experience and immerse in the content that they are watching.

PRACTICAL IMPLICATIONS

This study offers valuable insights for the media industry when making decisions about runtime and content format. For movie producers the significant positive effect on movie ratings suggests that allowing more time for an in-depth story leads to higher ratings. For television and streaming platforms the effect of duration on audience ratings is noticeably weaker and therefore implies that it may provide a benefit for TV episodes to be longer but not as much as it does for movies. Producers of episodic content should therefore consider whether additional runtime adds meaning to the experience of the viewer or risk losing interest of the viewer.

One limitation may be that audience ratings may be biased, such as some viewers may be more likely to leave a review when they only have very strong positive or negative opinions. Further research could include the variable genre and if this has an effect on the result.

CONCLUSION

The aim of this study was to explore how runtime influences audience ratings for movies compared to TV episodes, while controlling for release year. The variable "mruntimeMinutes" is mean-centered, and "startYearCentered" was centered around the year 1896, which serves as the baseline for interpretation. Using a multiple linear regression model, the analysis examined the effects of runtime, media type (movie vs. TV episode), and release year on audience ratings, including an interaction term between runtime and media type.

The results reveal a significant positive effect of runtime on audience ratings for movies (beta = 0.0076, p < .001), indicating that longer movies tend to receive higher ratings. The interaction between runtime and TV episode status is significant and negative (beta = –0.0044, p < .001), meaning that the positive effect of runtime on ratings is weaker for TV episodes than for movies. Nevertheless, the combined effect of runtime for TV episodes remains positive (0.0076 − 0.0044 = 0.0032), showing that longer episodes are still rated slightly higher on average. Additionally, a small but significant negative effect of release year suggests that, on average, more recent releases tend to have slightly lower ratings.

Overall, the findings indicate that runtime positively influences audience ratings across both media types, but the strength of this effect differs. Longer movies benefit more from extended runtimes than TV episodes, for which the improvement in ratings with increased runtime is more modest. This suggests that audiences may respond more favorably to longer runtimes in movies than in episodic content.