Exploring Factors Influencing Movie Success
Stat 184 Final Project

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Introduction

Movies are a huge part of our lives and a multi-billion-dollar industry that shapes and reflects society. With millions of people watching and reviewing films every year, the movie industry continues to evolve. Thousands of films are released annually, but only a few become truly successful. What factors contribute to a movie's success? Is it the genre, the budget, the actors, or something else? In this project, we set out to explore the elements that influence a movie's success by analyzing datasets of films and looking at trends in ratings, profits, and casting.

We are interested in this topic because movies are not only a major form of entertainment but also a massive industry. Understanding what leads to success can offer insights into both audience preferences and the strategies that shape film making today.

To guide our analysis, we focused on **three key research questions**:

1. How do audience ratings compare across the five most common movie genres?

2. Which top studios have the best return on investment, and is there a relationship between movie budget and profit?

3. Which stars appear most frequently in successful movies, and does the presence of specific stars tend to be linked to higher movie success?

Through these questions, we aim to uncover patterns and insights that explain what contributes to a movie's success. By comparing audience ratings across genres, we hope to identify which types of films tend to get the most viewers. Investigating studio performance and budget-profit relationships allows us to understand how financial decisions impact profitability. Finally, analyzing the presence of frequently featured stars helps us explore whether certain actors consistently appear in higher-performing films, potentially revealing a link between star presence and success. Overall, our goal is to better understand the creative and financial factors that shape successful movies.

Data Provenance

To explore the factors contributing to movie success, we used two well-sourced datasets that each provided different but complementary information from major online movie databases. We cleaned and combined these datasets through a detailed wrangling and merging process to create a final dataset. This merged version gave us the foundation needed to conduct a thorough Exploratory Data Analysis (EDA) and effectively address our research questions.

Before settling on these data sources, we evaluated multiple datasets. An earlier dataset **link the source of old?**, included many relevant attributes, but the newer ones offered more complete and consistent data, especially in financials and studio identifiers, making them a better fit for our analysis.

Main Dataset

Our main dataset was sourced from a **Github** repository created by the authors Tran Hieu Le, Totyana Hill, Fahim Ishrak and Zhilin Wang. It was originally scraped from TMDb (The Movie Database) this dataset contains information on approximately 5,000 movies released between the 1930s and 2016 (Hieu2695, 2019). Each *case* in the dataset represents a single movie, and includes essential attributes related to its financial performance and basic descriptors. The key *attributes* include production budget, worldwide revenue, title, production company, runtime, and genre. The *purpose* of collecting this data was to offer a structured overview of film financials, enabling analysis of profitability and return on investment.

Secondary Dataset

Our secondary dataset was obtained from **Kaggle** and published by Daniel Grijalva. It was originally scraped from IMDb and contains metadata on approximately 7,600 movies spanning from 1980 to 2020 (Grijalva, 2019). Each *case* corresponds to an individual movie and captures its descriptive, creative, and audience-related *attributes*. These include age rating, director, writer, lead actor (star), release year, rating count, and rating score. The *purpose* of this dataset was to supplement our main data by providing richer descriptive and audience-related information, which helped us better address our research questions.

Merged and Final Dataset

To answer our research questions, we combined our two datasets into a single, cleaned, and well-structured table. The datasets were merged based on matching *movie titles* and *production companies* to ensure accuracy and consistency. To maintain data quality, we excluded records with missing or invalid values and treated zero values in financial fields as missing. We also created a new variable, *Profit*, by subtracting budget from revenue to better assess the financial success in our analysis.

The final dataset includes movies released from 1980 to 2019, which aligns with the expected coverage based on the original time spans of the two source datasets. It contains 15 key attributes across essential categories: content (title, genre, runtime, rating), financials (budget, revenue,

profit), production details (studio, director, star), and audience reception (rating score and count). This comprehensive dataset provided a strong foundation to explore our research questions related to genre-based ratings, profit of companies, and the influence of star actors on a film's success.

FAIR and CARE Principles

The **FAIR** principles are essential for promoting high standards in data sharing, transparency, and long-term usability which our datasets do align to these guidelines.

- **Findable**: Our primary dataset was sourced from Kaggle and the secondary from GitHub, both of which are widely recognized platforms that provide basic metadata and descriptive tagging, making the data easy to locate.

- **Accessible**: Both datasets are publicly available and can be retrieved without login or payment barriers through standard web protocols. However, because the long-term availability of external repositories is not guaranteed, we also uploaded both original datasets as well as our cleaned and merged version to our own GitHub repository to ensure continued access and reproducibility.

- **Interoperable**: The datasets are provided in CSV format, a widely accepted and accessible format that enables easy integration into R and other data analysis tools, which insures smooth integration and analysis across various platforms.

- **Reusable**: The data includes meaningful attributes that provide context for interpretation. Through our cleaning and documentation process, we enhanced its structure, added derived variables like Profit, and clearly described the data's provenance, making it suitable for future research.

The **CARE** principles, focus on the ethical use of data for all people, especially for Indigenous or marginalized communities. While our datasets do not directly involve sensitive or community specific data, it's still important to reflect on these principles to ensure our work is thoughtful, fair, and respectful.

- **Collective Benefit**: Our project aims to uncover trends in the film industry that can help others better understand what drives movie success, whether creatively or financially. We hope our analysis supports open learning and sparks interest in data-driven storytelling.

- **Authority to Control**: The datasets we used weren't officially released by the platforms that host the data (IMDb, TMDb). That being said, they do algin with their terms and conditions of public usage.

- **Responsibility**: We made sure to treat the data with care. Since the dataset is non-sensitive and publicly accessible, we mainly focused on cleaning, organizing, and documenting it properly so our analysis would be accurate, transparent, and respectful.

- **Ethics**: We focused on minimizing harm by ensuring that our dataset did not include private or sensitive information and we avoided making claims that could misrepresent people or groups. We used the data strictly for educational purposes, and we made sure our work promoted fairness and transparency.

EDA: Exploratory Data Analysis

In our project, we implemented **Exploratory Data Analysis** to understand the structure of our datasets and uncover any errors or patterns before diving into deeper analysis. We began by cleaning and **wrangling** the data to ensure it was accurate and usable. This included identifying and removing rows with missing values (*NAs*), as well as fixing inconsistencies.

After cleaning the data, we created **frequency** and **summary tables** to examine key statistics such as the mean, median, and standard deviation, giving us a clearer picture of the overall distribution of variables like ratings. We then used **visualizations** to uncover patterns and relationships that weren't immediately apparent from the summary statistics alone.

Through EDA, we were able to detect irregularities in our dataset, gain a better understanding of its overall structure, and identify key trends that guided our analysis. This process provided a strong foundation for answering our research questions and exploring the factors that contribute to a movie's success.

Rating Distributions in the Five Most Common Genres

In this section, we will explore how audience ratings vary across the five most common movie genres. We begin by examining the summary statistics to better understand the distribution of ratings within each genre.

Summary Table

We created a **summary table** that highlights key statistics such as *film count, minimum, maximum, mean, median, standard deviation, and the 1st and 3rd quartiles*. This helps us better understand the distribution and variation in ratings across genres. Table 1 below showcases these statistics for the top genres.

Table 1: Summary Table of Ratings for the Top 5 Movie Genres

| Genre	FilmCount	MinRating	Q1Rating	MedianRating	Q3Rating	MeanRating	MaxRating	SdRating
Comedy	208	2.1	5.7	6.3	6.900	6.263942	8.8	0.9452131
Drama	207	4.1	6.4	7.0	7.500	6.906763	9.3	0.7832919
Action	199	3.7	5.8	6.3	6.900	6.301507	8.3	0.8837750
Adventure	94	4.7	6.1	6.5	7.275	6.563830	8.6	0.8893457
Horror	77	4.0	5.3	6.1	6.600	5.974026	8.1	0.9505404

Table 1 presents an overview of the ratings for the top five movie genres: Comedy, Drama, Action, Adventure, and Horror. Among these, **Drama** clearly stands out as the highest-rated genre, with a **mean rating** of **6.91**, a **median** of **7.0**, and a **maximum rating** of **9.3**. It also shows the most consistent performance, having the **lowest standard deviation** among all genres. In contrast, **Horror** ranks the lowest, with an **average rating** of **5.97** and the **widest spread** in ratings, indicating more variability in audience reception. The other genres fall in between, though **Adventure** shows a high level of variability similar to Horror.

When looking at film counts, **Comedy** and **Drama** are the most represented, each with over **200 films**, while **Horror** has the lowest count with just **77 films**, which may contribute to its greater rating variability.

Overall, the data suggests that Drama is both the most consistently high-performing genre and the best-rated on average, whereas Horror tends to be more unpredictable and generally receives lower ratings.

Box Plot

Figure 1 shows a box plot of the rating distributions for the top five movie genres. This visual helps us compare the typical ratings, variation, and presence of outliers across genres. It supports and expands on the summary statistics discussed earlier.

Figure 1: Distribution of Ratings for Top 5 Genres
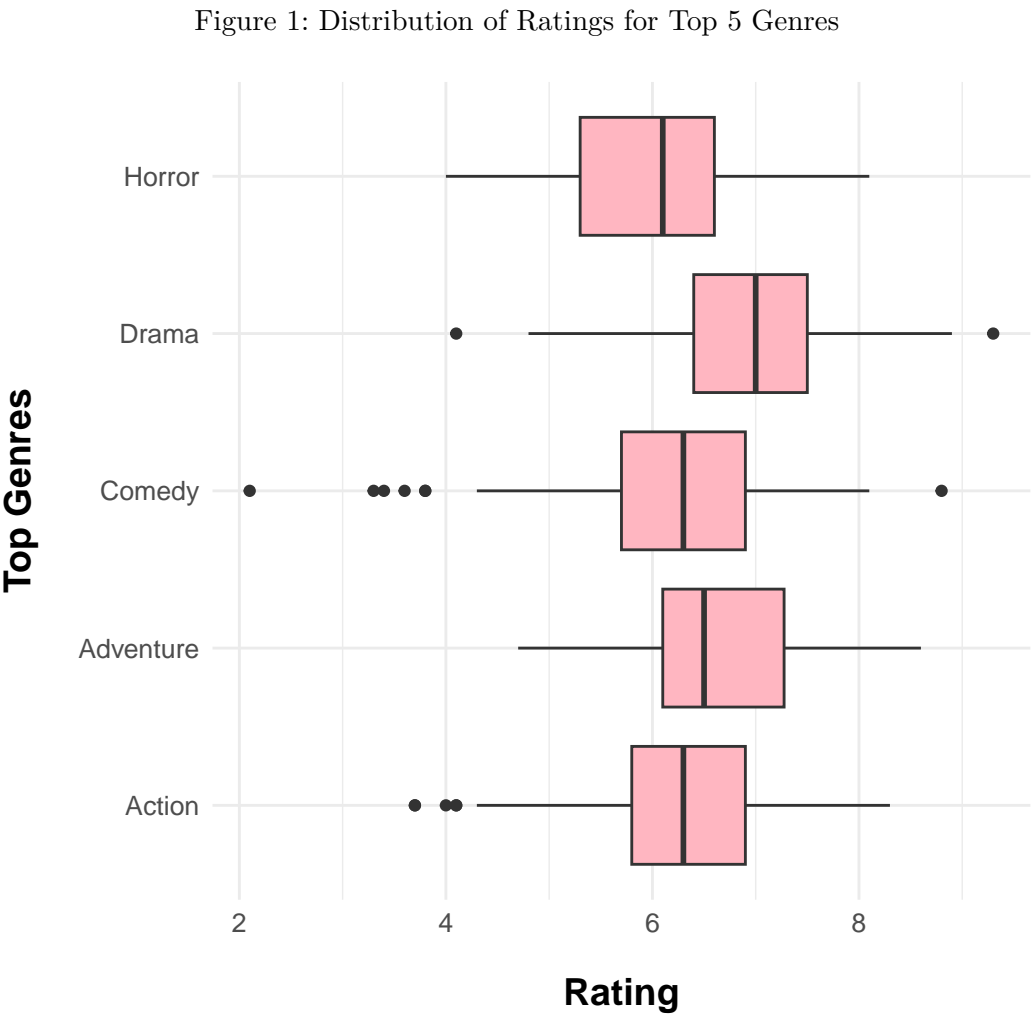
The box plot in Figure 1 shows the distribution of movie ratings across the top five genres and helps bring the numbers in Table 1 to life through a visual format. One thing that really stands out is how **Drama**'s entire box is shifted higher than the others, meaning that not only is its average rating high, but most of its movies consistently land in that higher range. It also has a **tighter**

interquartile range, meaning the ratings are tightly clustered, further reinforcing that Drama is the most consistent genre overall. In contrast, **Horror** displays a much wider spread, this suggests more variability in audience reception.

Comedy shows several low-rated *outliers* in the box plot, indicating that while many comedy films fall around the average, a few are rated significantly lower. According to the Summary Table 1, Comedy has a **minimum rating** of **2.1**, and the box plot confirms this value is a outlier with a point far below the lower whisker.

This highlights how a few poorly received films can drag down the overall average, even if most of the genre performs reasonably well. It's a reminder that summary statistics alone don't always tell the full story, without a visual, we wouldn't easily notice how rare or extreme those low ratings are. The visual helps us see that while these outliers exist, they are not representative of the genre as a whole.

Company Profitability and Financial Patterns

In this section, we will examine which top production studios generate the highest profits and whether there is a noticeable relationship between how much a company spends (**budget**) and how much it earns (**profit**). We began by identifying the **15 most active production companies** in our dataset, which we defined as those with the highest number of films. Focusing on these studios allowed us to base our comparisons on a solid number of films, making the patterns we observed more reliable.

Profit Bar Chart

EDIT

We began by calculating the average profit for each of the top 15 companies. To visualize this, we created a horizontal bar chart (Figure 2) that shows each company's name on the y-axis and its corresponding profit earnings in USD on the x-axis. The bars are sorted from lowest to highest average profit, allowing for a quick comparison of financial performance.

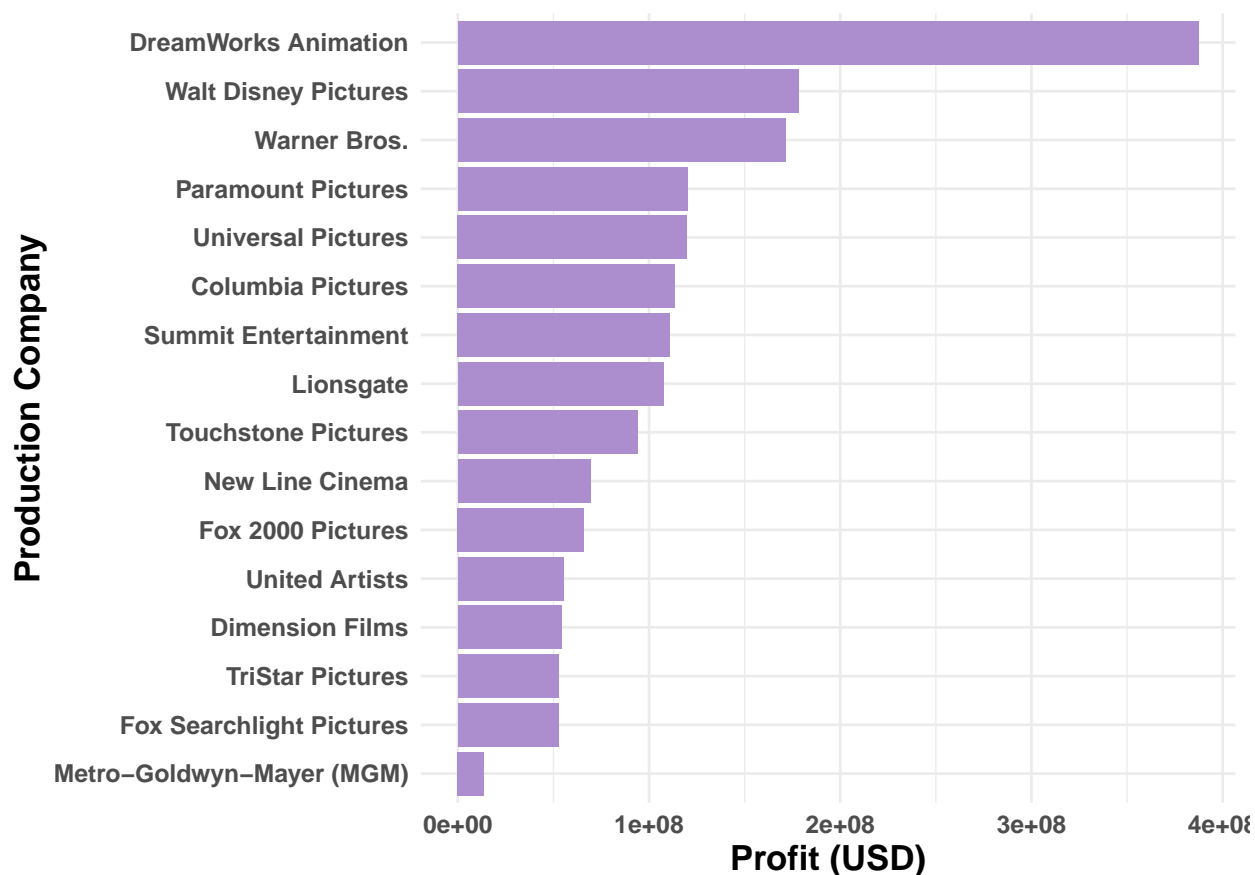Figure 2: Profit of the 15 Most Active Production Companies

Figure 2 shows a clear range of performance across companies. **DreamWorks Animation** leads, by a significant amount, with the highest profit among all production companies analyzed. This suggests that DreamWorks not only produces successful films but also does so consistently across its portfolio. Following DreamWorks are *Walt Disney Pictures* and *Warner Bros.* also show strong profits, indicating that these companies don't only have a strong industry presence but also a track record of producing very profitable movies. On the other hand, other active studios like Lionsgate and Columbia Pictures displayed more moderate profits, suggesting variability in the financial outcomes of their film portfolios. At the lower end of the chart, companies like *MGM* and *Fox Searchlight Pictures* have noticeably lower profits, suggesting either higher production costs or lower returns. The *gap* between top and bottom studios is significant, indicating that not all active companies achieve the same financial outcomes.

To sum up, this visualization helps highlight which studios are most effective in turning their investments into financial success and provides a high-level view of profitability trends across the industry.

Budget Bar Chart

We then looked at the production budget for films produced by the same top 15 active companies to determine whether higher investment levels are associated with higher profits. The results are

shown in Figure 3, a horizontal bar chart similar in structure to the profit chart, where each bar represents a company and their corresponding average budget in USD on the x-axis. Then, again, the bars are sorted from lowest to highest average budget. We can see in Figure 3, the results highlight some interesting differences.

Figure 3: Profit of the 15 Most Active Production Companies

Budget of the 15 Most Active Production Companies
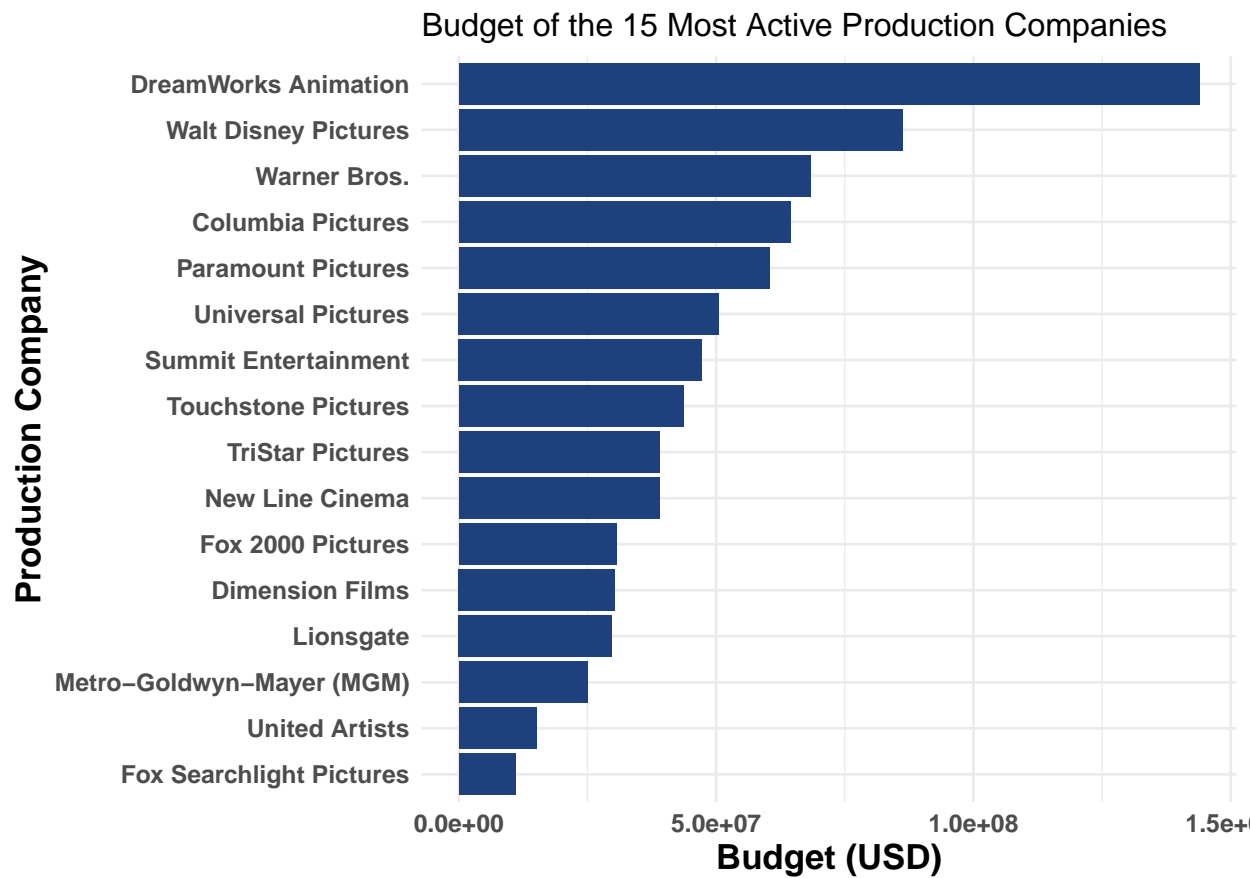
Budget vs. Profit Scatter Plot

Star Impact on Movie Success

To explore our third research question, examining which actors appear most frequently in movies and whether their presence contributes to a film's success. We defined success of movies in two distinct ways to deepen our analysis. The first definition focuses on **financial success** (Figure 4), measured by a profit exceeding $50 million. The second centers on **critical success** (Figure 5), evaluated through audience ratings. By analyzing how often the top five most frequent stars appear in successful films under each definition, we were able to identify consistent patterns and better understand the impact of star power on movie performance.

Summary Table

This Summary table presents statistics for the five most frequently appearing stars in the dataset. The columns include: **Movie Count** (the number of films each star appeared in), **Avg. Rating** (the average audience rating for those films), **Rating SD** (the standard deviation of ratings), and **Avg. Profit** (the average profit for the star's films). This table helps us begin exploring whether the most active stars tend to be in more successful films. In the following sections, we'll also visualize this data to examine whether their presence is linked to higher ratings or greater profitability.

Table 2: Summary Statistics for Top Stars

Star	Movie Count	Avg. Rating	Rating SD	Avg. Profit
Nicolas Cage	13	6.07	1.24	94028034
Adam Sandler	12	5.89	1.01	146358425
Dwayne Johnson	11	5.99	0.38	110519841
Tom Cruise	11	6.97	0.41	322109979
Tom Hanks	11	7.33	0.95	313617993

Table 2 shows that **Nicolas Cage** appears in the most films, with a total of **13**, but also has the *highest variability* in ratings, with a *standard deviation* of **1.24**, suggesting mixed audience responses. In contrast, **Dwayne Johnson** is the most consistent performer, with a *low standard deviation* of **0.38**, though his *average rating* is relatively normal at **5.99**. **Tom Hanks** stands out with the **highest average rating** of **7.33**, indicating that his films are well-received by viewers, along with a *high average profit.* **Tom Cruise** offers the strongest balance, combining a *high average rating* of **6.97** with the *highest average profit* in the group.

While these numbers reveal interesting patterns, we cannot confidently conclude that a star's presence directly affects a film's success. There may be other underlying factors at play that influence these outcomes. In fact, one possible influence could be **genre**. As seen in the box plot in Figure 1, **drama** films tend to receive the **highest ratings**, which could help explain *Tom Hanks'* strong performance. **Comedy** showed **greater variability** and several low-rated outliers, possibly contributing to *Adam Sandler's* lower ratings. **Action** films fall somewhere in the middle in terms of *rating consistency*, which may account for the **steadier results** seen with *Tom Cruise and Dwayne Johnson.* Meanwhile, *Nicolas Cage* has appeared across a wide range of genres, likely contributing to the **broader spread** in his ratings. However, further exploration will be needed to determine whether these patterns hold across a larger set of stars and whether other factors like genre play a more significant role.

Bar Chart

To dig deeper into financial success, we classified each movie as either "Successful" where the profit is more than $50 million or "Unsuccessful". Then created a bar chart showing the count of each category for the top five stars (Figure 4). The bars are color-coded: *teal* for successful films and *orange* for unsuccessful films.

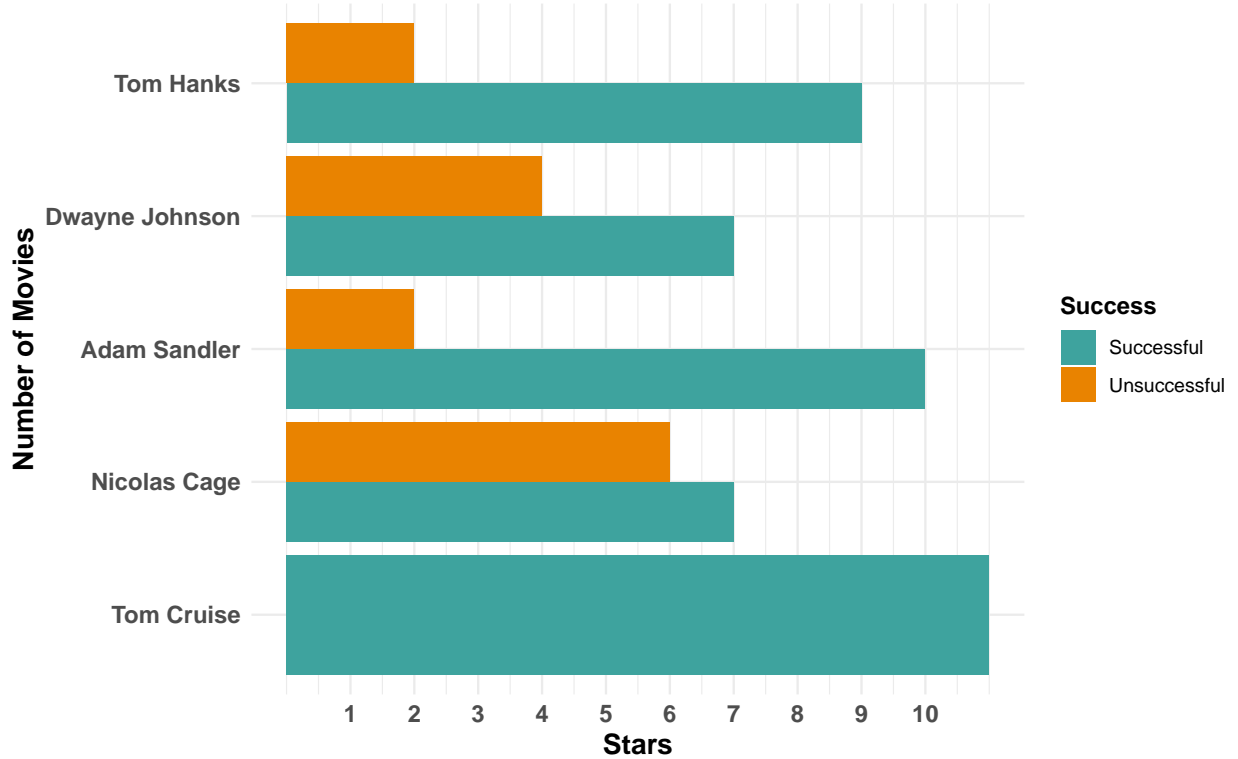Figure 4: Number of Successful Movies of Top 5 Most Frequent Stars

Figure 4 complements the earlier summary table (Table 2). We can see that all *13* of **Tom Cruise's** movies are considered successful under our definition, aligning with his position in the summary table, Table 2, as the star with the *highest average profit*. This consistency supports the idea that his presence in a film is a strong indicator of financial success for that film.

An interesting comparison arises between **Tom Hanks** and **Adam Sandler**, who both have two unsuccessful films, and Adam Sandler has just one more successful film (*10*) than Tom Hanks (*9*). Yet despite this, Table 2 shows that Tom Hanks has a significantly higher average profit, suggesting that the magnitude of financial success in Hanks's films is much greater—likely due to higher box office returns per film—even if he has fewer successes by count.

On the other hand, **Nicolas Cage**, who has the *lowest average profit*, also appears in the highest number of unsuccessful films (*6*), compared to *7* successful ones. This aligns with his broader performance variability. **Dwayne Johnson** sits in the middle, with a moderate average profit and a fairly balanced split: *7* successful and *4* unsuccessful films.

Together, Table 2 and Figure 4 provide a clearer understanding of the consistency of each star's success, not just how many movies they've made, but how often those movies perform well financially.

Scatter Plot

To better understand how audiences respond to the films of the most frequently featured stars, we created a scatterplot that maps the individual movie ratings for each of the top five actors

(Figure 5). Each point represents a single film, with its vertical position showing the audience rating and its color and shape identifying the star. This visualization allows us to look beyond averages and see the full range of how each star's movies are received, helping us explore whether certain actors consistently appear in higher-rated films or if their performance doesn't have much of an impact.

Figure 5: Movie Ratings of Top 5 Most Frequent Stars

In Figure 5, *Tom Hanks* clearly stands out, with all of his movies receiving **ratings above 6.0**, and several reaching as high as 8.5. This pattern reflects what we saw in the Summary Table 2, where he had the **highest average rating** overall. The cluster of tightly grouped, high ratings also suggests that his performances tend to be well-received.

In contrast, *Nicolas Cage*'s points are much more scattered, ranging from just over **3 to above 7**. This **wide spread** supports the **high standard deviation** shown in the Table 2 and illustrates the inconsistency in how his movies are rated by audiences. While he's been in some well-rated movies, he's also been in several that scored poorly.

Adam Sandler's ratings mostly fall in the mid range, with one movie below 4. This matches his **lower average rating** from **?@tbl-star** and shows that even though he appears in many films, they don't always perform well with audiences.

Tom Cruise has no ratings below 6, and most of his films land in a narrow range between **6.5 and 7.5**. This confirms what we saw earlier, he not only scores well but does so consistently, which could

be part of why his movies tend to be financially successful too. Similarly, *Dwayne Johnson*'s ratings are mostly **clustered around 6** with little spread, reflecting consistent but average performance.

Conclusion

To wrap up, our project investigated three main questions about what makes a movie successful. First, we examined how audience ratings differ across genres using Table 1 and Figure 1, and found that genres vary widely in performance. **Drama** had the *highest* and *most consistent ratings*, while **Horror** showed more *variability* and *lower scores*, with **Comedy** showing notable *outliers*. Second, we explored the relationship between production budgets and profits through @ (Profit by Company), @ (Budget by Company), and the Budget vs. Profit Scatter Plot (@). Together, these visuals suggest a *positive relationship between budget and profit*, where **higher investment** is often linked to **higher returns**. Lastly, in analyzing the impact of movie stars using Table 2, Figure 4 (Success Count), and Figure 5 (Ratings Scatterplot), we found that frequently appearing stars do not necessarily guarantee higher-rated or more profitable movies. While some stars like **Tom Cruise** and **Tom Hanks** show more consistent success, overall, our analysis **did not find strong evidence** that star presence alone drives movie success, more investigation would be needed to draw a firm conclusion. Overall, exploring these patterns helps deepen our understanding of what drives both critical and commercial success in the movie industry.

Sources and References

Main Dataset:

Hieu2695. (2019, November 5). Movie Industry [Data set]. GitHub. Retrieved May 6, 2025, from https://github.com/hieu2695/Movie-Industry/blob/master/Movie.csv

Supplemantry Dataset:

Grijalva, D. (2019, October). Movie Industry [Data set]. Retrieved May 6, 2025, from https://www.kaggle.com/datasets/danielgrijalvas/movies

Old Dataset:

Itiievskyi, I. (n.d.). IMDB Top 250 [Data set]. GitHub. Retrieved May 6, 2025, from https://github.com/itiievskyi/IMDB-Top-250/blob/master/imdb_top_250.csv

Code Appendix

```r
# Load all necessary packages -----
library(tidyverse)
library(rvest)
library(dplyr)
library(janitor)
library(knitr)
library(kableExtra)
library(ggplot2)

#Define global elements ----
psuPalette <- c("#1E407C", "#BC204B", "#3EA39E", "#E98300",
                "#999999", "#AC8DCE", "#F2665E", "#99CC00")


# Tidy and Merging the two datasets: ----

# Read Data ----
url1 <- "https://raw.githubusercontent.com/Stat184-Spring2025/Sec4_FP_Layan_Sara/main/Data/Budg
MoviesSubRaw <- read.csv(url1, header = TRUE)
url2 <- "https://raw.githubusercontent.com/Stat184-Spring2025/Sec4_FP_Layan_Sara/main/Data/Mov:
MoviesMainRaw <- read.csv(url2, header = TRUE)

# Tidying Secondary Movies data ----
# Filter out unwanted columns
MoviesSubTidy <- MoviesSubRaw %>%
  select(-c("released","budget","gross","genre","runtime"))

#Tidy the Main Movie data----
# Filter out unwanted columns
MoviesMainTidy <- MoviesMainRaw%>%
  select(-c("X","popularity", "release_date", "vote_average",
            "vote_count","Number_Genres"))

#Merging other two datasets----
MoviesJoined <- MoviesMainTidy%>%
  # Join by Title and Company
  inner_join(MoviesSubTidy, by = c("title"="name",
                                   "production_companies"="company") )%>%
  # Rename the columns
  rename(
    Title = title,
    Genre = genres,
    Company = `production_companies`,
    AgeRating= rating,
```

```r
      Year = year,
      Rating = score,
      RatingCount = votes,
      Director = director,
      Writer = writer,
      Star = star,
      Budget = budget,
      Revenue = revenue,
      RunTime= runtime,
      Country = country
  ) %>%
  # Re-order the columns
  select(Title, Genre, Company, AgeRating, Year,
          Rating, RatingCount, Director, Writer, Star, Budget, Revenue,
          RunTime, Country) %>%
  # Found two movies with revenues that are not in millions
  # Changed the two values
  mutate(
    Revenue = ifelse(Title == "Chasing Liberty", 12000000, Revenue),
    Revenue = ifelse(Title == "Death at a Funeral", 46000000, Revenue)
  ) %>%
  # Replace 0 with NA in Budget and Revenue
  mutate(
    Budget = ifelse(Budget == 0, NA, Budget),
    Revenue = ifelse(Revenue == 0, NA, Revenue)
  ) %>%
  # Make a Profit column
  mutate(Profit = Revenue-Budget) %>%
  # Replace "Not Rated" and "Unrated" in AgeRating with NA
  mutate(
    AgeRating = ifelse(AgeRating %in% c("Not Rated", "Unrated"),
                        NA, AgeRating)
  ) %>%
  # Drop rows with missing Budget, Revenue, or AgeRating
  drop_na(Budget, Revenue, AgeRating)

# Create a csv file and save it
#write.csv(
#  MoviesJoined,
#  file = "MoviesJoined.csv",
#  row.names = FALSE
#)


# Read the joined dataset ----
basePart <- "https://raw.githubusercontent.com/Stat184-Spring2025/"
mainPart <- "Sec4_FP_Layan_Sara/main/Data/MoviesJoined.csv"
```

```r
url <- paste0(basePart,mainPart)
MoviesJoined <- read.csv(url, header = TRUE)

# Creating a summary table of Ratings by Genres ----

Genre_summary <- MoviesJoined%>%
  group_by(Genre)%>%       # Groups the data by Genre column
  summarise(               # Calculates summary statistics for each genre
    FilmCount = n(),       # Number of films in each genre
    MinRating = min(Rating, na.rm = TRUE),    #Minimum rating (ignores NA values)
    Q1Rating = quantile(Rating, 0.25, na.rm = TRUE),  # First quartile
    MedianRating = median(Rating, na.rm = TRUE),      # Median rating
    Q3Rating = quantile(Rating, 0.75, na.rm = TRUE),  # Third quartile
    MeanRating = mean(Rating, na.rm = TRUE),     # Mean (average) rating
    MaxRating = max(Rating, na.rm = TRUE),       # Maximum rating
    SdRating = sd(Rating, na.rm = TRUE)          # Standard deviation of ratings
  ) %>%
  arrange(desc(FilmCount))%>%        # Sorts the genres by film count
  slice_head(n=5)        # Selects the top 5 movie genres with the most films

# Displaying the summary table ----
Genre_summary%>%
  kable(
    booktabs = TRUE,
    align = c("l", rep("c",8)), # Left-aligns the first column, centers the rest
    format = "latex"
  )%>%
  kableExtra::kable_styling(
    font_size = 16,           # Sets font size of the table
    latex_options = c("striped","scale_down"),
  )%>%
  row_spec(0, bold = TRUE, background = "pink")%>%  # Styles the header
  column_spec(1, italic = TRUE) # Styles the 1 column

# Wrangling Box Plot Data ----
## Get Top 5 Genres
TopGenres <- MoviesJoined %>%
  count(Genre, sort = TRUE) %>% # Counts num of movies per genre and sorts them
  slice_max(order_by = n, n = 5) %>%  # Selects top 5 genres w most movies
  pull(Genre)

## Show data for only the Top 5 genres
MovieGenre <- MoviesJoined %>%
  filter(Genre %in% TopGenres)  # Filter movies of only the top 5 genres


# Create the box plot for Genre and Ratings----
```

```r
ggplot(
  data = MovieGenre,
  mapping = aes(
    x = Rating,        # Set the x-axis to represent Rating
    y = Genre      # Set the y-axis to represent Genre
  )
) +
geom_boxplot(fill = "lightpink") +    # Creates box plot with pink boxes
labs(
  y = "Top Genres",    #labels the x axis
  x = "Rating"      #labels the y axis
) +
theme_minimal()+
theme(
  text = element_text(size = 12),
  axis.title.x = element_text(face = "bold",    # Make the x-axis title bold
                              size = 14,      # Set font size to 14
                              margin = margin(t = 15)
                              ),
  axis.title.y = element_text(face = "bold",
                              size = 14,
                              margin = margin(r = 15)
                              )    # margin pushes titles away from axis
)


# Creating visualizations for 2nd Question ----

# Get top 15 companies by number of movies
TopCompanies <- MoviesJoined %>%
  count(Company, sort = TRUE) %>%
  slice_max(n, n = 15) %>%
  pull(Company)

#Create the Profit Bar Chart -----
#Get the average Profit for the Companies
CompanyProfit <- MoviesJoined %>%
  group_by(Company) %>%
  summarize(AverageProfit = mean(Profit, na.rm = TRUE)) %>%
  ungroup()

CompanyProfit %>%
  filter(Company %in% TopCompanies) %>%
  ggplot(aes(x = reorder(Company, AverageProfit), #Sort the bars by profit
             y = AverageProfit)) +
  geom_col(fill = "#AC8DCE") +
  coord_flip() + #Make it horizontal
  #Label axes
```

```r
  labs(
    x = "Production Company",
    y = "Profit (USD)"
  ) +
  theme_minimal() +
  theme(
    axis.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 10, face = "bold")
  )


#Create the Budget Bar Chart -----
#Calculate Average Budget per Company
CompanyBudget <- MoviesJoined %>%
  group_by(Company) %>%
  summarize(AverageBudget = mean(Budget, na.rm = TRUE)) %>%
  ungroup()
#Filter to top companies and plot
CompanyBudget %>%
  filter(Company %in% TopCompanies) %>%
  ggplot(aes(x = reorder(Company, AverageBudget), y = AverageBudget)) +
  geom_col(fill = "#1E407C") +
  coord_flip() +
  labs(
    title = "Budget of the 15 Most Active Production Companies",
    x = "Production Company",
    y = "Budget (USD)"
  ) +
  theme_minimal() +
  theme(
    axis.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 10, face = "bold")
  )

# Wrangling Star Summary Table Data ----
star_summary <- MoviesJoined %>%
  group_by(Star) %>%  # Group data by each unique star
  summarise(
    Movie_Count = n(),      # Count number of movies each star appeared in
    Avg_Rating = mean(Rating, na.rm = TRUE), # Calculate the average rating
    SD_Rating = sd(Rating, na.rm = TRUE), # Standard deviation of ratings
    Avg_Profit = mean(Profit, na.rm = TRUE) # Average profit per movie
  ) %>%
  arrange(desc(Movie_Count))%>%      # Sort stars by number of movies
  slice_head(n=5)%>%    # Keeps only the top 5 most frequent stars
  mutate(across(where(is.numeric), round, 2)) # Rounds to 2 decimal places
```

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```r
# Displaying the Summary Table ----
star_summary %>%
  kable(booktabs = TRUE,
        col.names = c("Star", "Movie Count", "Avg. Rating",
                      "Rating SD", "Avg. Profit"), # Names columns
        align = c("l", rep("c", 4)), # Align first column left, others center
        format = "latex" # Output the table in LaTeX format (for PDF rendering)
  )%>%
  kableExtra::kable_styling(
    font_size = 16,              # Sets font size of the table
    latex_options = c("striped","scale_down") # Apply striped rows
  )%>%
  row_spec(0, bold = TRUE)  # Bold the header row

# Wrangling ScatterPlot of the Rating for Top Stars ----

# Identify Top 5 Stars by number of movies
top5_stars <- MoviesJoined %>%
  count(Star, sort = TRUE) %>%  # Count how many times each star appears
  slice_head(n = 5) %>%  # Keep the top 5 most frequent stars
  pull(Star)

# Filter movies for those stars
top_star_movies <- MoviesJoined %>%
  filter(Star %in% top5_stars)

# Create Bar Chart of Successful movies -----
MoviesJoined %>%
  # Define Success in movies as Profit > $50M
  mutate(Success = ifelse(Profit > 50000000, "Successful", "Unsuccessful")) %>%
  # Take the Top 5 Stars
  filter(Star %in% top5_stars) %>%
  # Get their counts
  count(Star, Success) %>%
  ggplot(aes(x = n,
             y = reorder(Star, -n),
             fill = Success)) +
  geom_bar(stat = "identity",
           position = "dodge") + # Set the bars side to side
  scale_x_continuous(breaks = 1:10) + # Number the x-axis
  scale_fill_manual(values = c("Successful" = "#3EA39E",
                               "Unsuccessful" = "#E98300")) +
  labs(
    x = "Stars",
    y = "Number of Movies") +
  theme_minimal() +
  theme(
```

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    legend.title = element_text(face = "bold"),
    axis.title = element_text(size = 13, face = "bold"),
    axis.text = element_text(size = 11, face = "bold")
  )



# Plot the Scatterplot of Stars/Rating ----

ggplot(
  data = top_star_movies, # Use the filtered dataset
  mapping = aes(x = Star,     # X-axis shows the star's name
                y = Rating,   # Y-axis shows the movie rating
                color = Star,   # Color points by star for distinction
                shape = Star # Shape for star distinction
                )
  ) +
  geom_jitter(width = 0.2, size = 3) +
  scale_color_manual(values = psuPalette) +  # Apply custom colors
  labs(
    x = "Star",   # X-axis label
    y = "Movie Rating",  # Y-axis label
    color = "Top Stars Name",
    shape = "Top Stars Name"
  ) +
  theme_minimal() +     # Uses a clean, minimal theme
  theme(
    legend.position = "right",  # Place the legend on the right
    legend.title = element_text(size = 14, face ="bold"),  # Set legend text size and bolds
    legend.text = element_text(size = 13),
    axis.title.x = element_text(face = "bold",   # Make the x-axis title bold
                                size = 15,     # Set font size to 14
                                margin = margin(t = 15)
                                ),
    axis.title.y = element_text(face = "bold", # Customize y-axis title
                                size = 15,
                                margin = margin(r = 15)
                                ),
    axis.text = element_text(size = 12, face = "bold")
  ) # margin pushes title away from axis
```