

Hollywood by the Numbers: Trends from The Movies Dataset

Presented by: Group 5iveCoders



Starring...



Ifrah

The film is never
the same the
second or ..the
hundredth time



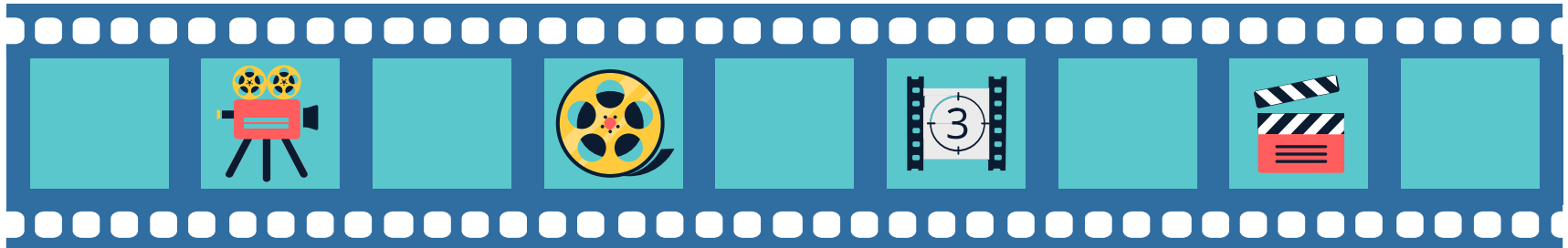
Manny

Mercury is the
smallest planet in
the Solar System



Tin

Hot Take:
Antitrust is a good
movie!



Trouble in Paradise



We originally scoped our project to analyze the impact of tourism on local economies and environments.

We ran into issues:

- Multiple datasets that required combining
- No single large dataset
- Data entry would have been required for PDF based reports
- Limited Scope on Data/Reporting

```
Economy
What is the share of tourism in the GDP of a specific region or country?
What is the correlation between total tourism employment and a country's overall GDP?
How does the employment in tourism vary among top countries?

Environmental
Is there a collation of higher CO2 Emissions with countries with high tourism?
Are countries more likely to be sustainable with tourism, based on popularity?
--

Tourism Data:
Top 10 Countries based on Arrivals
Top 10 Countries with highest tourism revenue
Top 10 Countries with most tourism spending
- https://pre-webunwto.s3.eu-west-1.amazonaws.com/s3fs-public/2024-06/Barom_PPT_May_2024.pdf?VersionId=U7062Hat1G4eNAJ.wcmuQG1PMCjK.Yss
- https://en.wikipedia.org/wiki/World_Tourism_rankings

Top 10 Outbound
Top 10 Tourism Revenue, % of GDP
How does revenue from international tourists compare to domestic tourists?
What percentage of the local GDP is contributed by the tourism industry?

Economy Data:
How many jobs are created in tourism-related sectors (e.g., hospitality, transportation, retail)?

https://www.oecd.org/en/data/indicators/tourism-employment.html
https://data.worldbank.org/indicator/SL.IND.EMPL.ZS
https://www.cia.gov/the-world-factbook/field/labor-force/
https://www.statista.com/statistics/292490/contribution-of-travel-and-tourism-to-employment-in-selected-countries/
https://www.reportlinker.com/dataset/cdc57592680361cd78b8ee1b4206c09e121f728b
https://www.nationmaster.com/xx/ranking/total-tourism-employment
https://www.unwto.org/tourism-statistics/economic-contribution-SDG

How does spending vary between international and domestic tourists?
https://www.statista.com/statistics/207089/forecast-of-travel-expenditures-in-the-us
https://ourworldindata.org/grapher/average-expenditures-of-international-tourists-domestically?tab=table

Environmental Data:
Trend in total waste compared to top tourism countries
https://datatopics.worldbank.org/what-a-waste/
https://www.unwto.org/tourism-statistics/economic-contribution-SDG
https://ourworldindata.org/grapher/implementation-of-tools-to-monitor-economic-and-environmental-tourism
https://ourworldindata.org/co2-and-greenhouse-gas-emissions#explore-data-on-co2-and-greenhouse-gas-emissions

Are there signs of overtourism in certain destinations (e.g., overcrowding, pollution, strain on infrastructure)?
https://moneytransfers.com/news/2023/09/06/the-most-and-least-over-touristed-destinations-around-the-world
https://www.cnn.com/travel/2023-worst-destinations-overtourism-avoid-crowds/index.html
```

The Movies Dataset



The Movies Dataset

Metadata on over 45,000 movies. 26 million ratings from over 270,000 users.



[Data Card](#) [Code \(666\)](#) [Discussion \(41\)](#) [Suggestions \(2\)](#)

About Dataset

Context

These files contain metadata for all 45,000 movies listed in the Full MovieLens Dataset. The dataset consists of movies released on or before July 2017. Data points include cast, crew, plot keywords, budget, revenue, posters, release dates, languages, production companies, countries, TMDb vote counts and vote averages.

This dataset also has files containing 26 million ratings from 270,000 users for all 45,000 movies. Ratings are on a scale of 1-5 and have been obtained from the official GroupLens website.

Content

This dataset consists of the following files:

movies_metadata.csv: The main Movies Metadata file. Contains information on 45,000 movies featured in the Full MovieLens dataset. Features include posters, backdrops, budget, revenue, release dates, languages, production countries and companies.

keywords.csv: Contains the movie plot keywords for our MovieLens movies. Available in the form of a stringified JSON Object.

credits.csv: Consists of Cast and Crew Information for all our movies. Available in the form of a stringified JSON Object.

links.csv: The file that contains the TMDb and IMDb IDs of all the movies featured in the Full MovieLens dataset.

links_small.csv: Contains the TMDb and IMDb IDs of a small subset of 9,000 movies of the Full Dataset.

Usability ⓘ
8.24

License
CC0: Public Domain

Expected update frequency
Not specified

Tags

Earth and Nature
Movies and TV Shows
Popular Culture

After evaluating our original scope, we decided to pivot and found the The Movies Dataset

Factors that enable our decision:

- Single Dataset with multiple CSVs
 - 45,000 Movies
 - 26 Million Ratings
- No Data Entry Required
- OMDb and TMDb APIs to support data
- A lot of opportunity for deeper analysis

Discovering Trends with the Movies Dataset

1

Most Common Genres

In the last decade

2

Directors

With the highest IMDb rating

3

Movie Runtimes

Are they getting longer or shorter?

4

Actors

Who appears the most frequent in high-rated movies?



Movie Budgets

Does more money mean better movies?

5

Country Origin

Which countries are producing the most films?

6

Genre Revenue

Which genre creates the most revenue?

7

Genre Profit

Genre's revenue correlate to its profitability?

8

Question 1:

What are the most common movie genres released over the years?

The dataset we used, `metadata_movies.csv` included movies released as far back as 1990. To simplify the visualization, we focused on movies from the last decades.

The `genres` column was originally in dictionary format, so we converted it into a list of genre names for easier processing. The transformation applied was:

```
cleaned_movies_df["genres"] =  
cleaned_movies_df["genres"].apply(lambda x: x  
if isinstance(x, list) else [])  
  
cleaned_movies_df["genres"] = cleaned_movies_df["  
genres"].apply(lambda x: [i["name"] for i in x]  
if isinstance(x, list) else [])
```

genres
[{"id": 16, "name": "Animation"}, {"id": 35, "name": "Comedy"}]
[{"id": 12, "name": "Adventure"}, {"id": 14, "name": "Family"}]
[{"id": 10749, "name": "Romance"}, {"id": 35, "name": "Comedy"}]
[{"id": 35, "name": "Comedy"}, {"id": 18, "name": "Drama"}]
[{"id": 35, "name": "Comedy"}]



genres
[Animation, Comedy, Family]
[Adventure, Fantasy, Family]
[Romance, Comedy]
[Comedy, Drama, Romance]
[Comedy]

Question 1:

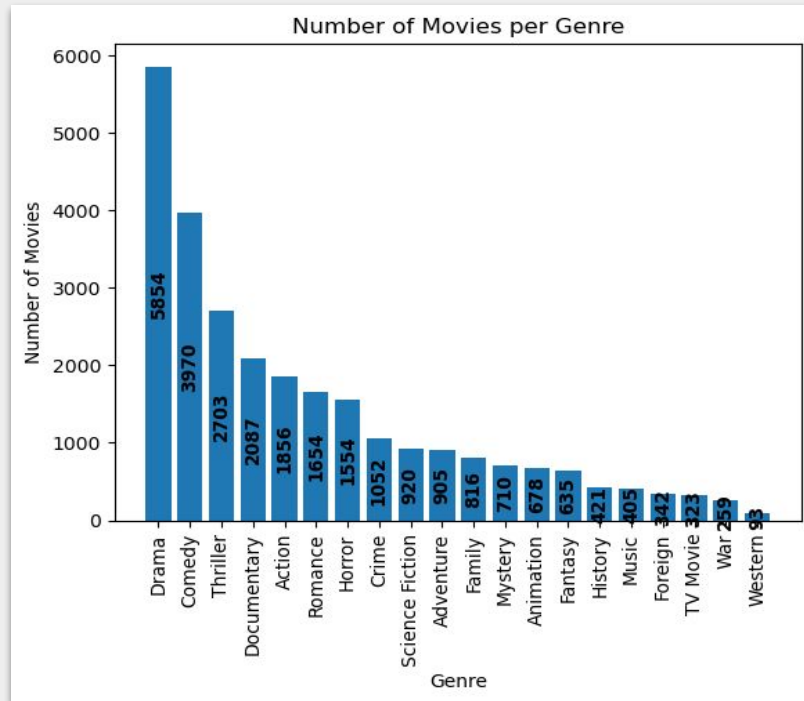
What are the most common movie genres released over the years? (cont.)

Flattened the `genres` list to count how many movies were released per genre over the years.

```
# Flatten the 'genres' list and count occurrences

genre_counts =
last_decade_movies_df['genres'].explode().value_counts()
# Create a DataFrame with the genre counts
genre_counts_df =
pd.DataFrame(genre_counts).reset_index()
genre_counts_df.columns = ['genre', 'count']
genre_counts_df.head(20)
```

The bar graph shows Drama and Comedy as the most released genres in the last decade.



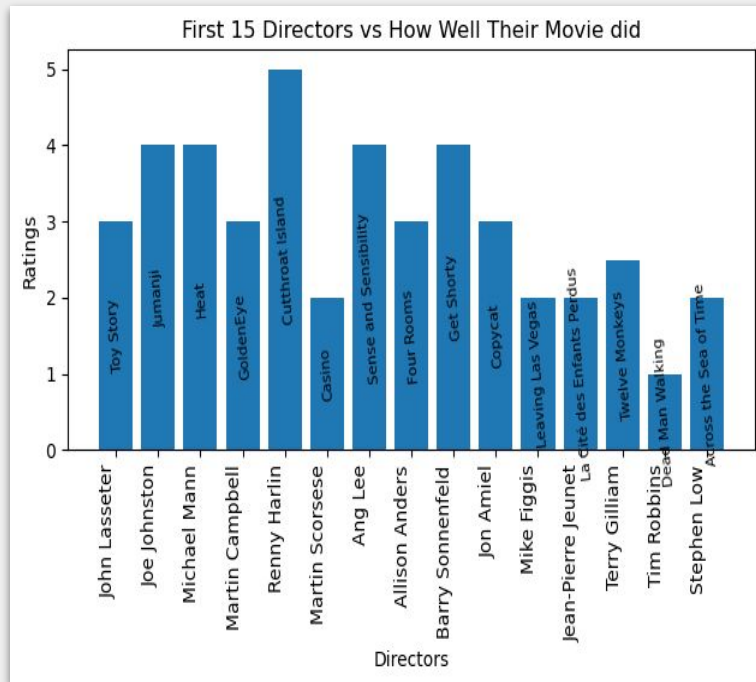
Question 2:

Which directors have the highest average IMDb ratings across their films?

Imported data from various .csv files(credits, ratings, movies.metadata) to merge into one Final_rating_df,DataFrame, to get the first 15 Directors and the imdb_rating for their movies.

Shortcoming:

Sorting ratings in ascending order gave us, the 5.0 ratings of all directors, hence no disparity to go off by thus only going by the first 15_Directors.



Question 2:

Which directors have the highest average IMDb ratings across their films? (cont).

To get more information on the movie with the highest rating, i did an API search:

```
api_key= "&apikey=" + "99b7bf4e"  
url="https://www.omdbapi.com/?t="  
response=requests.get(url +  
first_rating_df.iloc[4,3] + api_key)  
data=response.json()  
pprint(data)
```

Hence knowing that:

The Movie Cutthroat Island, was released in 22 Dec 1995, got 1 nomination total and had a Box Office total of: \$10,017,322.

```
{'Actors': 'Geena Davis, Matthew Modine, Frank Langella',  
'Awards': '1 nomination total',  
'BoxOffice': '$10,017,322',  
'Country': 'France, Italy, Germany, United States',  
'DVD': 'N/A',  
'Director': 'Renny Harlin',  
'Genre': 'Action, Adventure, Comedy',  
'Language': 'English, Spanish, Latin, French',  
'Metascore': '37',  
'Plot': 'A female pirate and her companion race against their rivals to find "  
        "a hidden island that contains a fabulous treasure.",  
'Poster': 'https://m.media-amazon.com/images/M/M558ZT020WY2N1ct0T4yN500MThjJlYyZjE5N  
'Production': 'N/A',  
'Rated': 'PG-13',  
'Ratings': [{'Source': 'Internet Movie Database', 'Value': '5.7/10'},  
             {'Source': 'Rotten Tomatoes', 'Value': '40%'},  
             {'Source': 'Metacritic', 'Value': '37/100'}],  
'Released': '22 Dec 1995',  
'Response': 'True',  
'Runtime': '124 min',  
'Title': 'Cutthroat Island',  
'Type': 'movie',  
'Website': 'N/A',  
'Writer': 'Michael Frost Beckner, James Gorman, Bruce A. Evans',  
'Year': '1995',  
'imdbID': 'tt0112760',  
'imdbRating': '5.7',  
'imdbVotes': '31,478'}
```

Question 3:

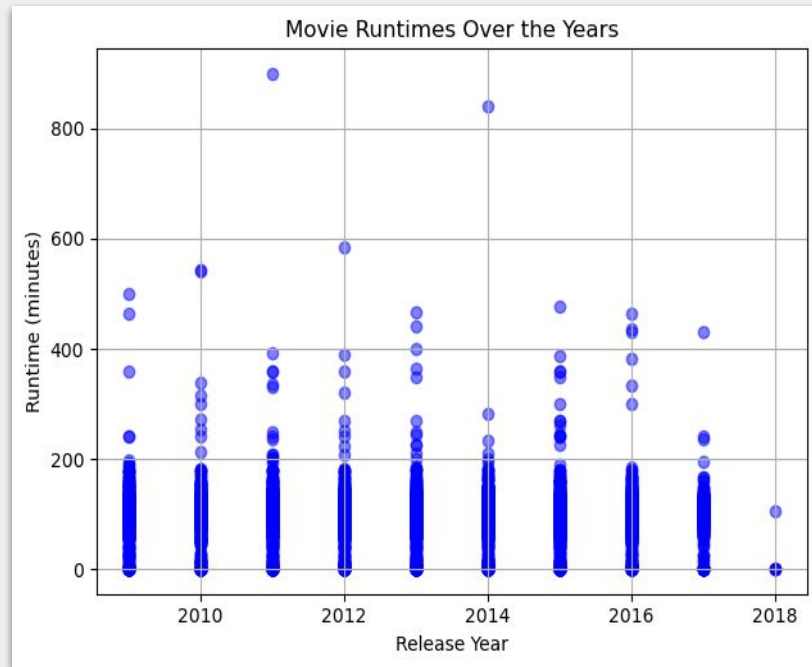
What is the trend of movie runtimes over the years?

```
#convert release date to datetime format
cleaned_movies_df["release_date"] = pd.to_datetime(cleaned_movies_df["release_date"], errors="coerce")
cleaned_movies_df["release_date"] = cleaned_movies_df["release_date"].dt.year
```

To answer the question, we converted the release date column to a year-only format.

Using `movie_metadata`, we created a DataFrame with release dates and runtimes for all movies.

Conclusion: Movie runtimes are slightly shorter but not significantly enough to raise concern.



Question 4:

Which actors appear most frequently in high-rated movies?

We worked with two datasets:

`metadata_movies.csv` and `credits.csv`.

To connect IMDb rating data with the actors listed in the credits dataset, we had to handle the `cast` column, which contained a list of dictionaries for each film.

Due to the large number of actors, we narrowed our focus to the top 5 actors for each movie and stored them in a separate column.

```
[{'cast_id': 14, 'character': 'Woody (voice)', 'credit_id': '52fe4284c3a36847f8024f95', 'gender': 2, 'id': 31, 'name': 'Tom Hanks', 'order': 1, 'profile_path': '/profile_path/52fe4284c3a36847f8024f99', 'gender': 2, 'id': 12898, 'name': 'Tim Allen', 'order': 1, 'profile_path': '/profile_path/52fe4284c3a36847f8024f99'}, {'cast_id': 1, 'character': 'Alan Parrish', 'credit_id': '52fe44bfc3a36847f80a7c73', 'gender': 2, 'id': 2157, 'name': 'Robin Williams', 'order': 1, 'profile_path': '/profile_path/52fe44bfc3a36847f80a7c99', 'gender': 2, 'id': 8537, 'name': 'Jonathan Hyde', 'order': 2, 'profile_path': '/profile_path/52fe44bfc3a36847f80a7c99'}, {'cast_id': 2, 'character': 'Max Goldman', 'credit_id': '52fe466a9251416c75077a8d', 'gender': 2, 'id': 6837, 'name': 'Vance Colvig', 'order': 1, 'profile_path': '/profile_path/52fe466a9251416c75077a91', 'gender': 2, 'id': 3151, 'name': 'Jack Lemmon', 'order': 1, 'profile_path': '/profile_path/52fe466a9251416c75077a91'}, {'cast_id': 1, 'character': 'Savannah Vannah Jackson', 'credit_id': '52fe44779251416c91011aad', 'gender': 1, 'id': 8851, 'name': 'Nancy Travis', 'order': 1, 'profile_path': '/profile_path/52fe44779251416c91011ab1', 'gender': 1, 'id': 9780, 'name': 'Angela Bassett', 'order': 2, 'profile_path': '/profile_path/52fe44779251416c91011ab1'}, {'cast_id': 1, 'character': 'George Banks', 'credit_id': '52fe44959251416c75039eb9', 'gender': 2, 'id': 67773, 'name': 'Nancy Travis', 'order': 1, 'profile_path': '/profile_path/52fe44959251416c75039ebd', 'gender': 1, 'id': 3092, 'name': 'Diane Keaton', 'order': 1, 'profile_path': '/profile_path/52fe44959251416c75039ebd'}]
```

id	actor_1	actor_2	actor_3	actor_4	actor_5
862	Tom Hanks	Tim Allen	Don Rickles	Jim Varney	Wallace Shawn
8844	Robin Williams	Jonathan Hyde	Kirsten Dunst	Bradley Pierce	Bonnie Hunt
15602	Walter Matthau	Jack Lemmon	Ann-Margret	Sophia Loren	Daryl Hannah
31357	Whitney Houston	Angela Bassett	Loretta Devine	Lela Rochon	Gregory Hines
11862	Steve Martin	Diane Keaton	Martin Short	Kimberly Williams-Paisley	George Newbern

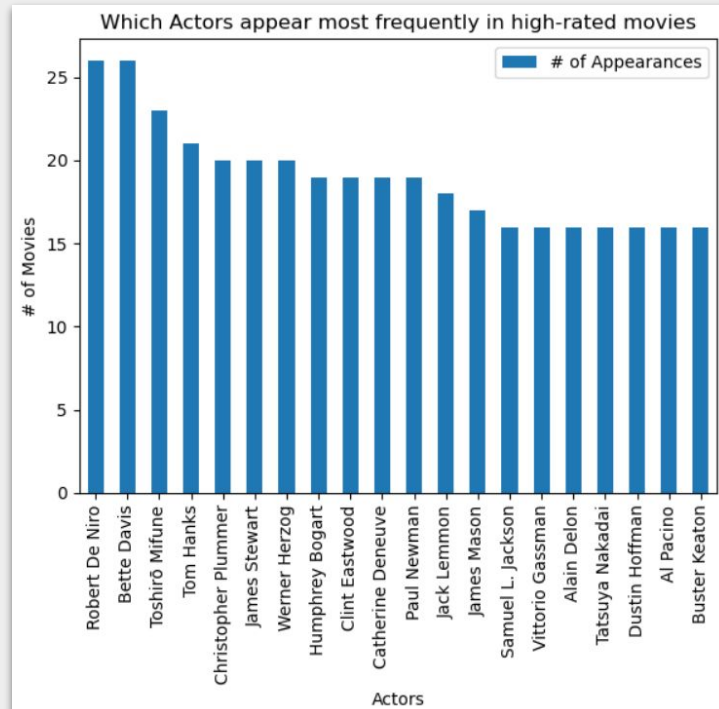
Question 4:

Which actors appear most frequently in high-rated movies? (cont.)

```
# Putting the 5 actors into their own column with a repeating ID
merged_movie_df = merged_movie_df.melt(
    id_vars=['id', 'imdb_id', 'original_title', 'release_date', 'title',
            'vote_average', 'vote_count'],
    value_vars=['actor_1', 'actor_2', 'actor_3', 'actor_4', 'actor_5'],
    value_name='actor'
)
```

```
# Applying Vote Average Filter
filtered_merged_movie_df =
merged_movie_df[merged_movie_df['vote_average'] > 7]
actor_appearance_counts =
filtered_merged_movie_df['actor'].value_counts()
```

```
# Display the top 20 actors
actor_appearance_counts_df = actor_appearance_counts.reset_index()
actor_appearance_counts_df.columns = ['actor', 'appearance_count']
actor_appearance_counts_df.rename(columns={'actor': 'Actor',
            'appearance_count': '# of Appearances'}, inplace=True)
actor_appearance_counts_df.head(20)
```



Question 4:

Which actors appear most frequently in high-rated movies? (cont.)

Robert De Niro starred in the movie,
The Godfather Part II.

It was released in 18 Dec 1974 and it grossed
a box office of \$47,834,595 with an IMDb
rating of 8.3.



```
imdb_id = filtered_actor.loc[filtered_actor['title']  
== 'The Godfather: Part II', 'imdb_id'].values[0]
```

```
movie_actors = data['Actors'].split(", ")  
target_movie_actor = movie_actors[1]  
movie_title = data['Title']  
movie_actor = data['Actors'][1]  
movie_boxoffice = data['BoxOffice']  
imdb_rating =  
filtered_actor.loc[filtered_actor['title'] == 'The  
Godfather: Part II', 'vote_average'].values[0]  
release_date = data['Released']
```

Question 5:

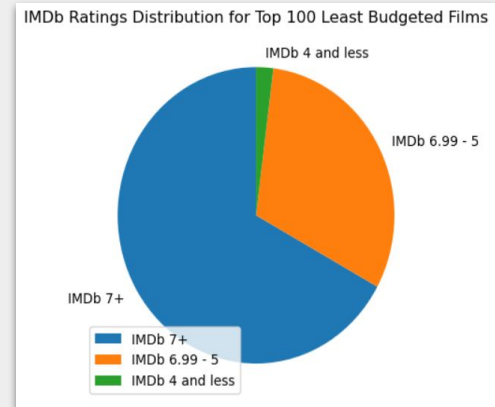
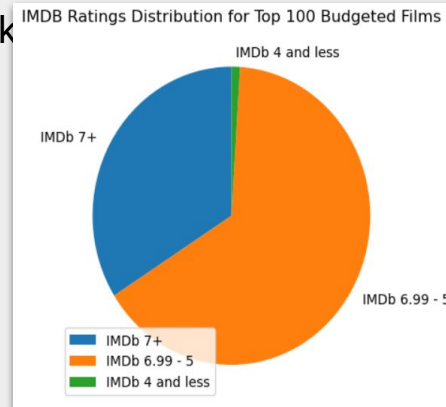
How does budget correlate with IMDb rating?

We worked solely in the `metadata_movies.csv`.

To understand trends in budget, we decided to work with the top 100 movies with the most and least budget.

The scores were grouped into 3 categories to showcase overall spread of the data.

Based on our finding, we were able to see that budgets with the least budget had a higher percentage of a higher rating.



Question 5:

How does budget correlate with IMDb rating? (cont.)

We used the OMDb API to gather additional information on our two movies.

Most budgeted film with a poor rating

The movie **Independence Day: Resurgence** had a budget of **\$165,000,000**. Their Box Office was **\$103,144,286** with an IMDb rating of **4.9**.

Plot: **Two decades after the first Independence Day invasion, Earth is faced with a new extra-Solar threat. But will mankind's new space defenses be enough?**

Least budgeted film with the okay rating

The movie **Paranormal Activity** had a budget of **\$15,000**. Their Box Office was **\$107,918,810** with an IMDb rating of **5.9**.

Plot: **After moving into a suburban home, a couple becomes increasingly disturbed by a nightly demonic presence.**

Question 5:

How does budget correlate with IMDb rating? (cont.)

We used the OMDb API to gather additional information on our two movies.

Most budgeted film with a poor rating

```
movie_title = data['Title']
movie_budget = topscores_4andless_df['budget'].iloc[0]
movie_boxoffice = data['BoxOffice']
imdb_rating = topscores_4andless_df['vote_average'].iloc[0]
movie_plot = data['Plot']
```

```
print(f'The movie {movie_title} had a budget of  
${movie_budget:,}. Their Box Office was {movie_boxoffice}  
with an IMDb rating of {imdb_rating}.')
print('')
print(f'Plot: {movie_plot}')
```

Least budgeted film with the okay rating

```
movie_title = data['Title']
movie_budget = bottomscores_6thru5_df['budget'].iloc[0]
movie_boxoffice = data['BoxOffice']
imdb_rating = bottomscores_6thru5_df['vote_average'].iloc[0]
movie_plot = data['Plot']
```

```
print(f'The movie {movie_title} had a budget of  
${movie_budget:,}. Their Box Office was {movie_boxoffice}  
with an IMDb rating of {imdb_rating}.')
print('')
print(f'Plot: {movie_plot}')
```


Question 6

Which countries produce the most amount of movies in each genre?

The focus of the last 3 questions was on movie production as well as financial performance. We decided to focus on the data set `metamovies_dataset.csv` as it contained information over a vast arrays of categories.

Cleaning this data allowed us to narrow our focus on the most relevant columns and gain insights into all of these questions.

```
# Drop columns with unneeded data.
```

```
clean_movies_metadata_df = movies_metadata_df.drop(columns=["adult",  
"poster_path", "production_companies", "belongs_to_collection",  
"homepage", "original_language", "original_title", "overview",  
"release_date", "runtime", "spoken_languages", "status",  
"tagline", "video"])
```

```
clean_movies_metadata_df
```

```
#drop rows with missing values
```

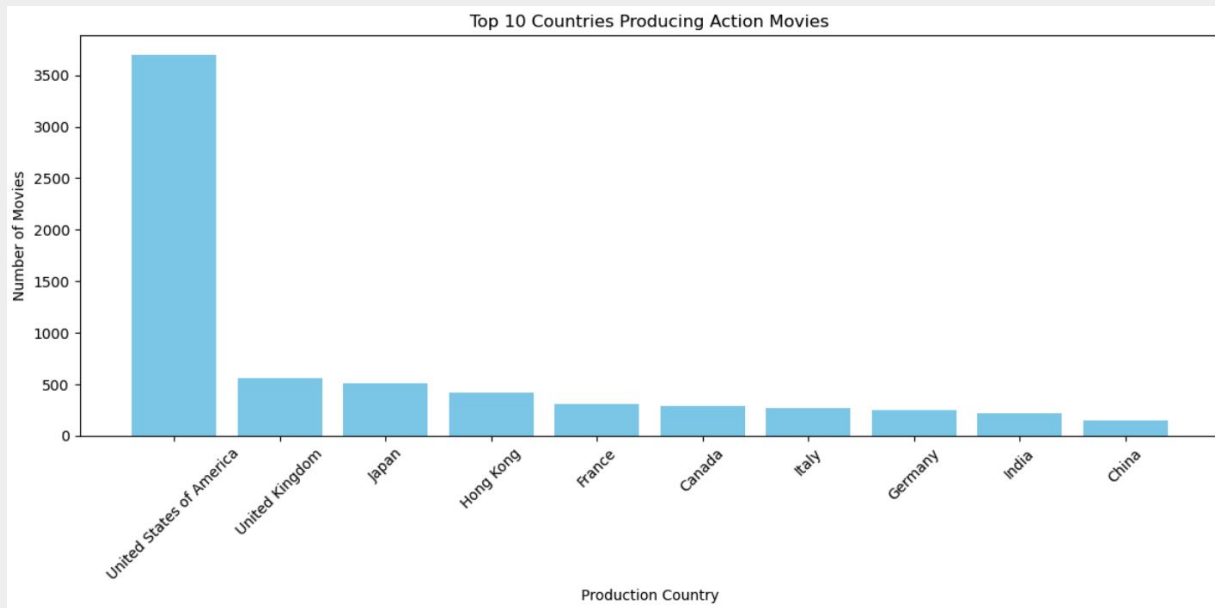
```
clean_movies_metadata_df=clean_movies_metadata_df.dropna()  
clean_movies_metadata_df=clean_movies_metadata_df.dropna(axis=1,)
```

```
clean_movies_metadata_df
```

Result

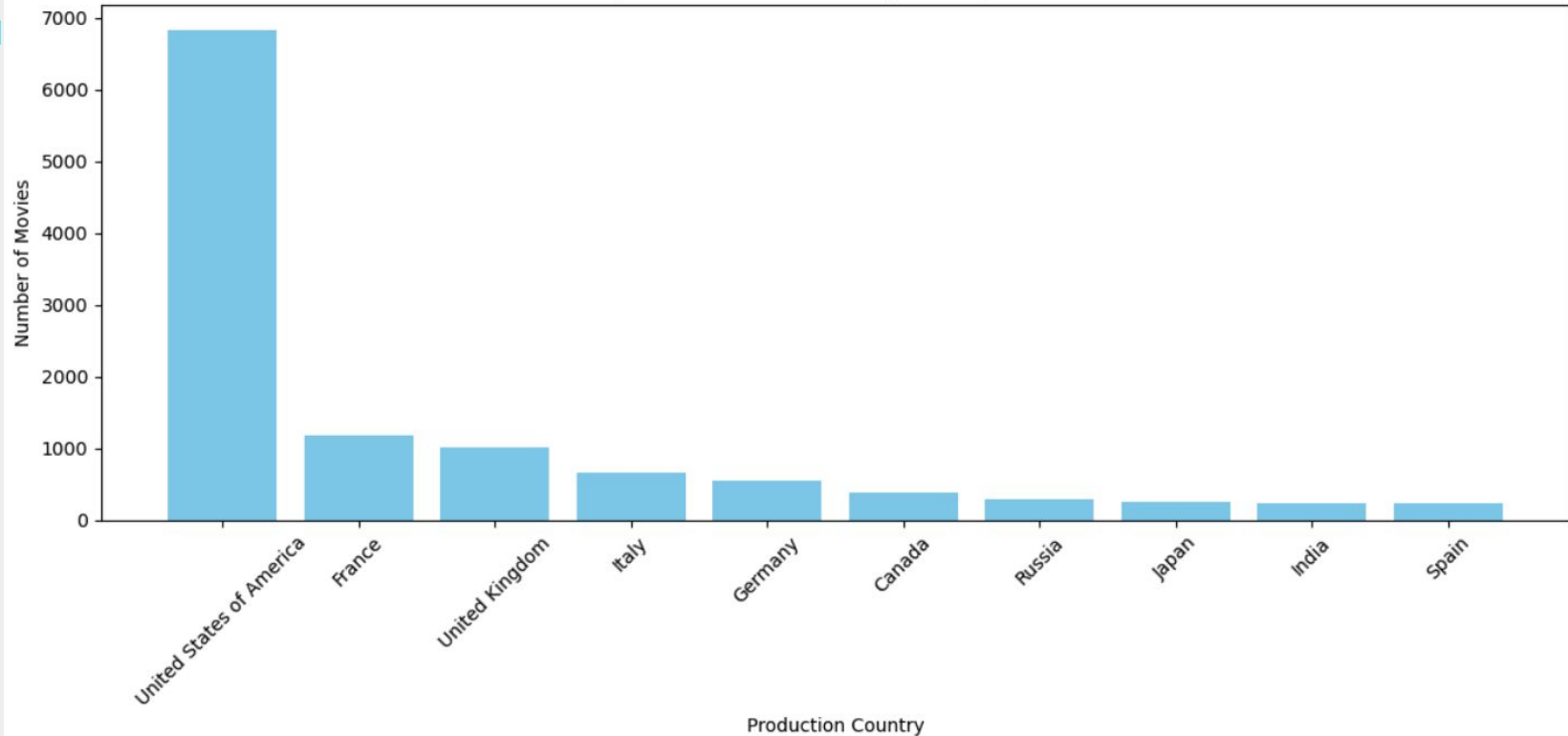
The U.S. leads in the amount of movie productions across every category but the rest of the genres are mainly produced in France, Italy, Germany, Japan and The U.K.

Action Movies



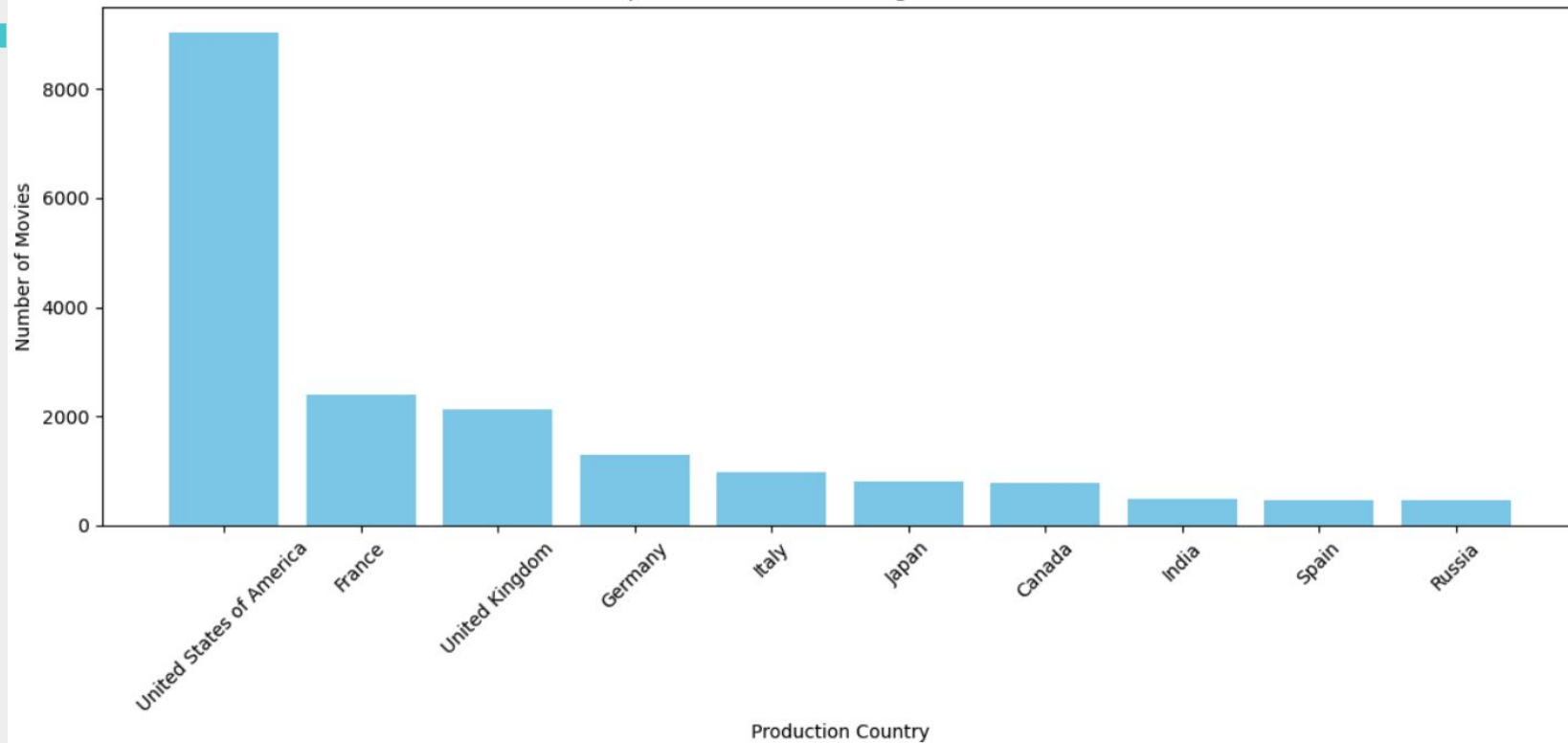
Comedy

Top 10 Countries Producing Comedy Movies



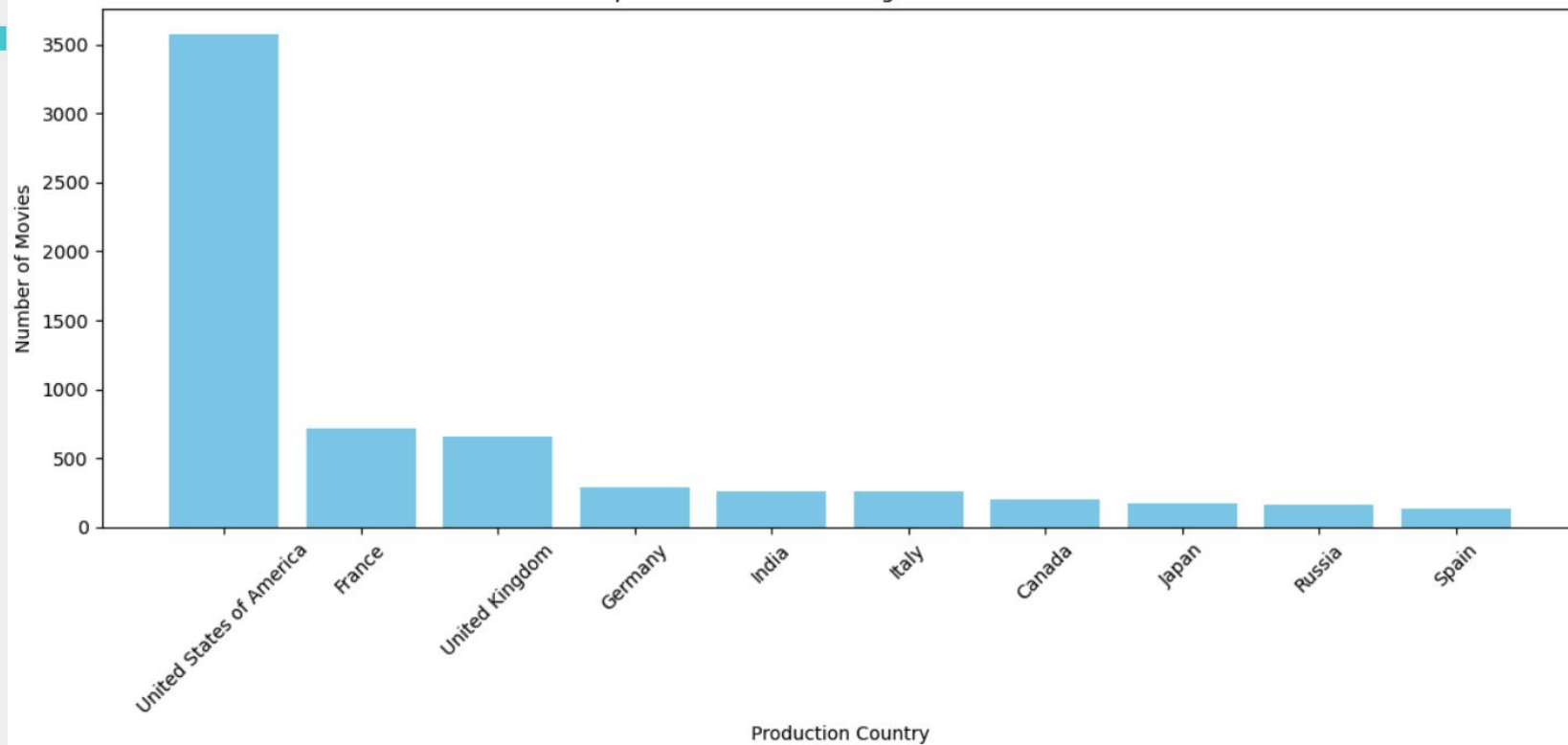
Drama

Top 10 Countries Producing Drama Movies



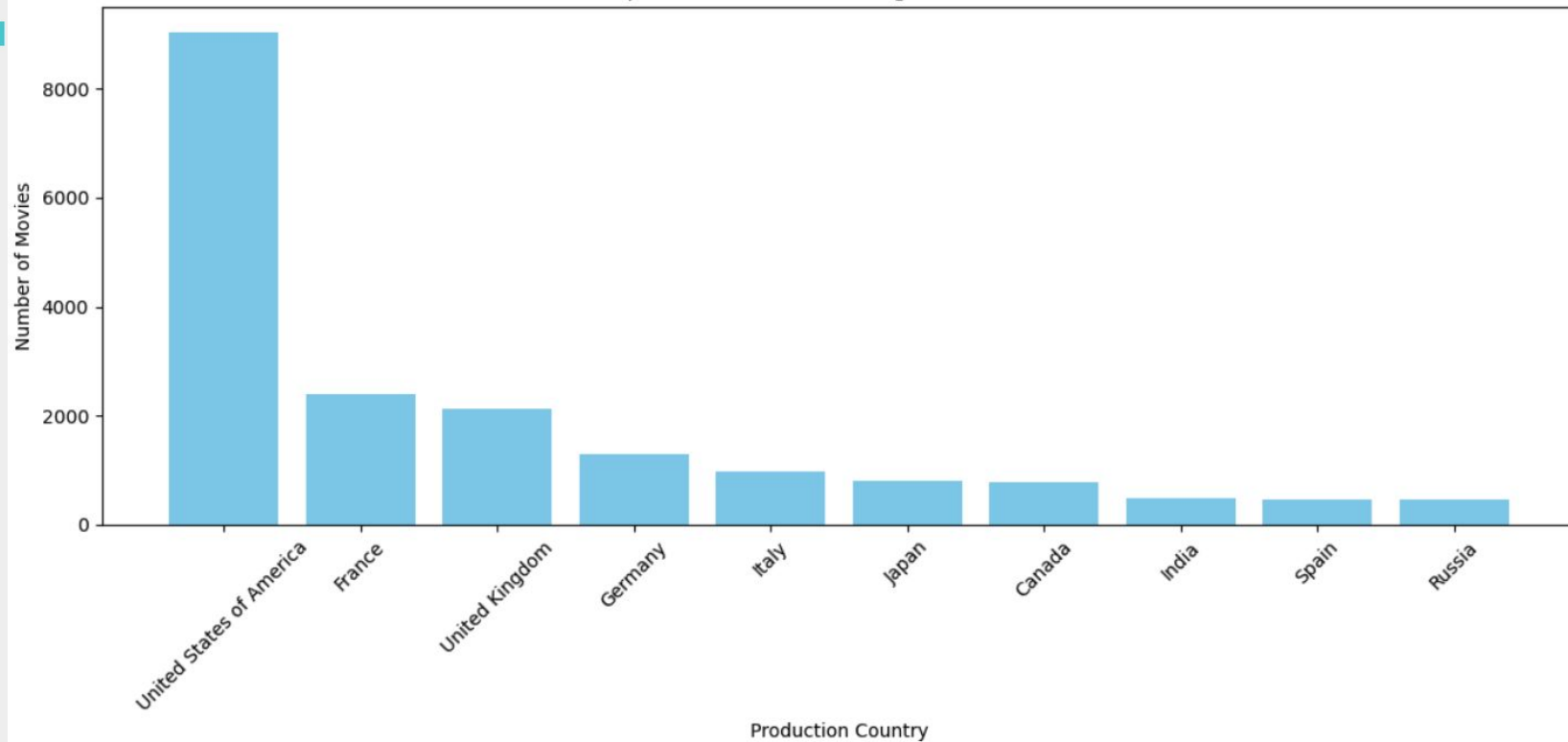
Romance

Top 10 Countries Producing Romance Movies



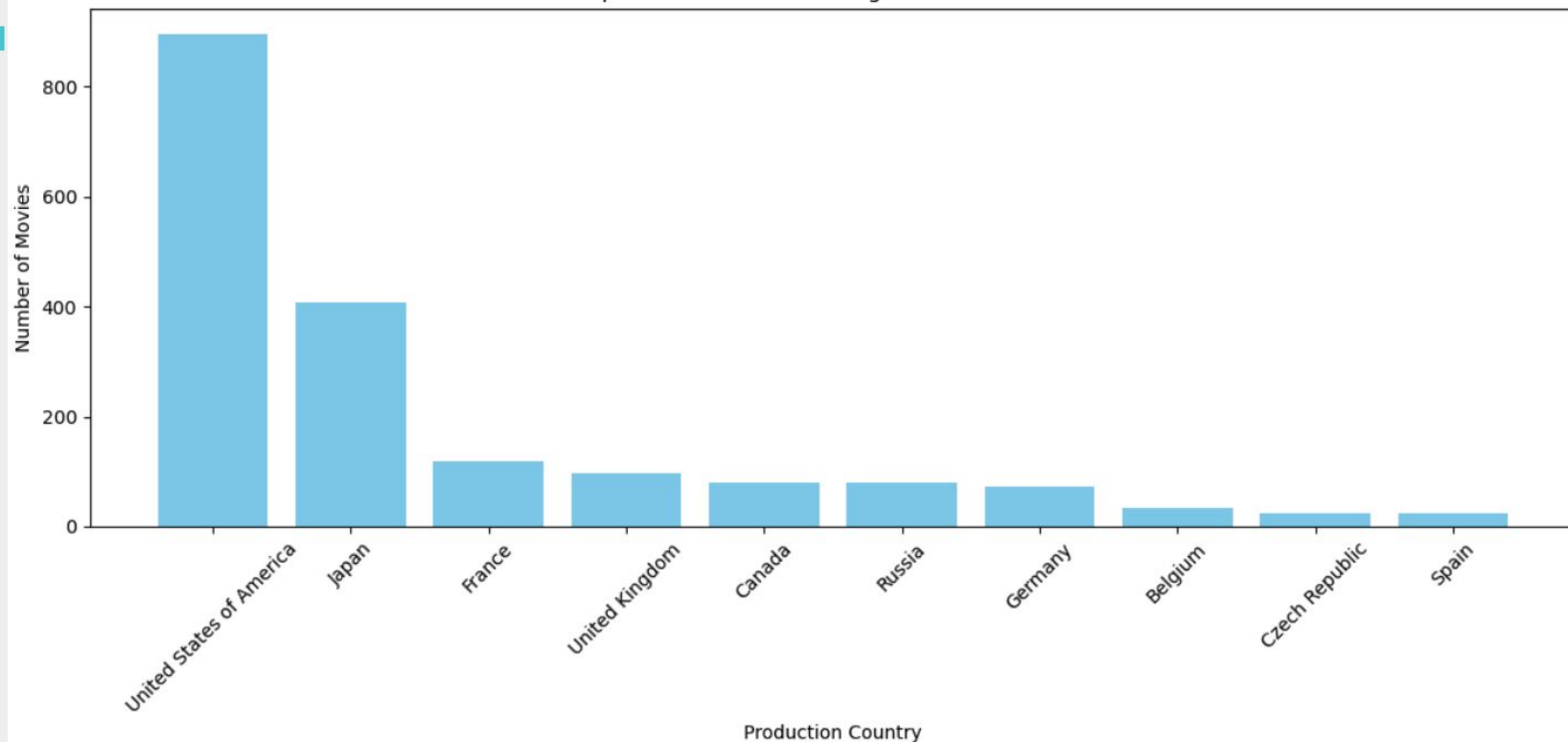
Drama

Top 10 Countries Producing Drama Movies



Animation

Top 10 Countries Producing Animation Movies



Question 7

On average, which movie genre generates the most revenue?

With the increased sophistication and uses of new technologies, movies today look and feel better than ever. We wanted to know how this is reflected in the revenue generated by each genre.

```
cleaned_metadata_df =
```

```
cleaned_metadata_df[(cleaned_metadata_df
```

```
!=0) .all(axis=1)]
```

```
revenue_by_genre_df = cleaned_metadata_df
```

```
.groupby("Genres")["Revenue"].mean().reset_index()
```

Working with the same data set

`metamovies_dataset.csv` we did some more cleaning, grouped movies by genres and calculated the mean of the different categories.

```
revenue_by_genre_df["Average Revenue by Genre"] =
```

```
round(revenue_by_genre_df["Average Revenue by Genre"],
```

```
1)
```

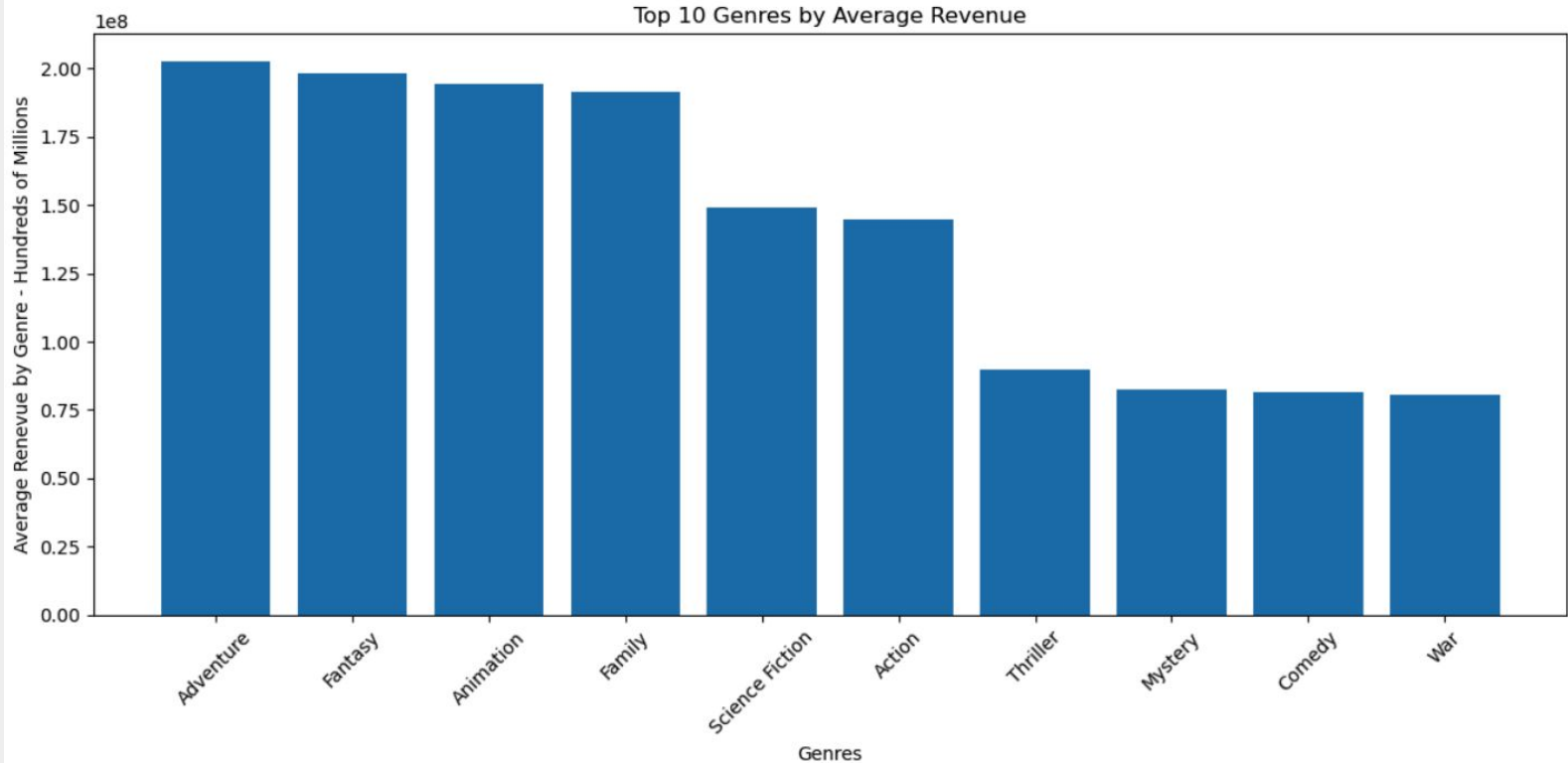
Average Revenue by Genre
2.024051e+08
1.979628e+08
1.941754e+08
1.914142e+08
1.488569e+08
1.444742e+08
8.991798e+07
8.257412e+07



Average Revenue by Genre
202405064.6
197962826.4
194175414.1
191414211.8
148856896.9
144474234.8
89917976.7
82574121.2

Result

While comedy brings in as much revenue as mystery films, the adventure genre has doubled their performance in recent decades.

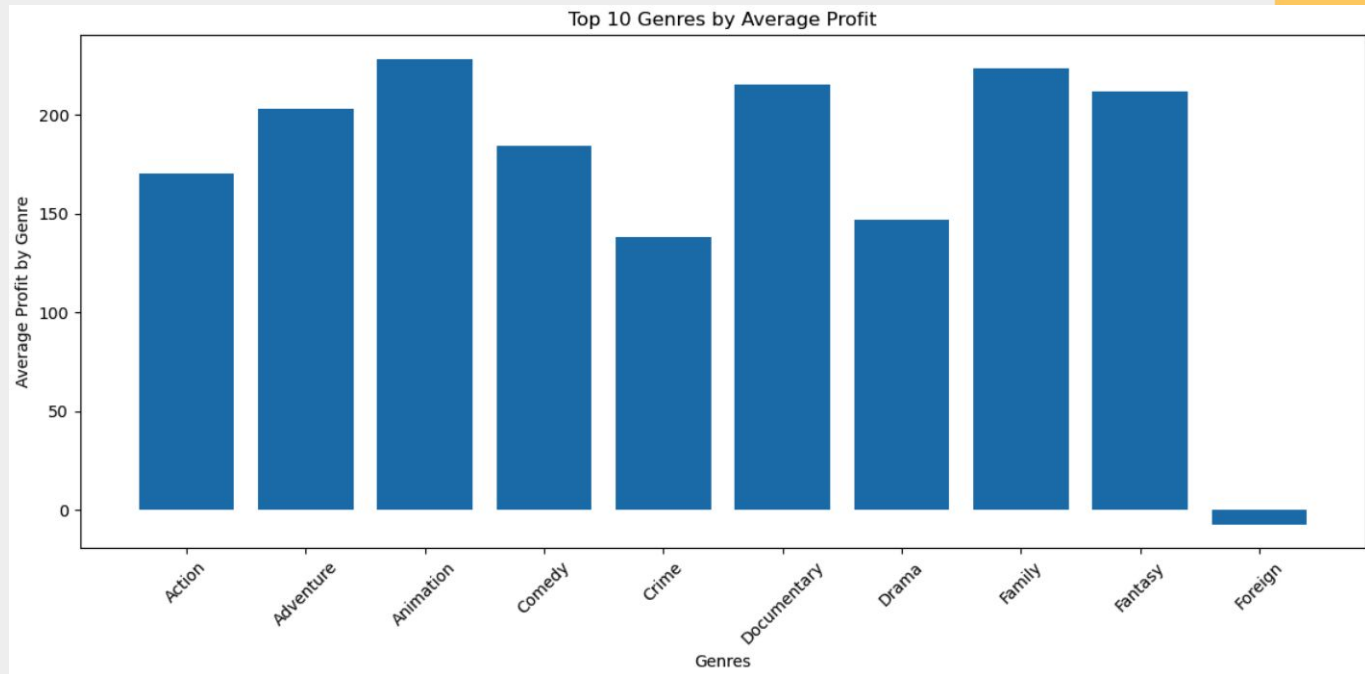


Question 8

Does a genre's revenue correlate to its profitability?

Result: They do!

While movie production is highly profitable across the board, the family, adventure and animation genres tend to bring the most revenue as well as the highest average profits at over 200%.





fin.